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An object based land use classification of Singapore using Definiens Developer

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Abbreviations

DEM	Digital Elevation Model
GCP	Geographic Control Point
GIS	Geographic Information System
GLCM	Grey Level Co-occurrence Matrix
ISODATA	Iterative Self-Organizing Data Analysis Technique
IPCC	Intergovernmental Panel on Climate Change
MD	Minimum Distance
MIR	Middle Infrared
MLC	Maximum Likelihood Classification
MMU	Minimum Mapping Unit
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Differenced Water Index
NIR	Near Infrared
OBIA	Object Based Image Analysis
REDD	Reducing Emissions from Deforestation and forest Degradation
RS	Remote Sensing

Abstract

The aim of this master's thesis is to generate a land use map of Singapore based an object oriented classification approach. Spot 5 satellite data is classified using the "Definiens Developer 7" software. The given satellite image provides a resolution of 2.5 meters in the panchromatic mode and 10 meters in the multispectral mode. The pixels of a remote sensing image are merged into image objects with a segmentation algorithm. The grouping of pixels is based on spectral and shape characteristics of nearby pixels. The resulting image objects differ with regard to color, shape, size and texture. Furthermore, the software takes the neighborhood relationships of the image objects into account.

A rule set based on thresholds and neighborhood relationships is build up for the classification of the land cover. The land use information is derived from the land cover classification. The land use classes are based on the IPCC top-level classes "forest land", "cropland", "wetland", "settlement" and "other land". Additionally the class "no data" is introduced. These classes were defined in the "Good Practice Guidance for Land Use, Land-Use Change and Forestry" report of 2003. These classes were adopted for the classification approach within the Singapore project.

The quality of the classification result is evaluated with an accuracy assessment. Random points are created on the basis of the classification of the satellite data with the "ArcMap" software. Each random point is situated on an image object and the class information of this image object is stored for each point. The class of the points is compared to their position in the "ArcMap" basemap. The basemap provides worldwide satellite or aerial imagery data and is offered within the "ArcMap" software. A visual interpretation process is applied to detect the class information of the "ArcMap" basemap for each random point. With the information of the classification of the random points and their membership in the reference data the error matrix is built up. The error matrix calculates the producer, user and overall accuracy. On the basis of these accuracies a statement with regard to the quality of the classification result can be made and the suitability of the object based classification approach for the task.

Zusammenfassung

Die vorliegende Masterarbeit beschäftigt sich mit der Erstellung einer Landnutzungskartierung für das Untersuchungsgebiet von Singapur. Die Software „Definiens Developer 7“ wird verwendet, um die zur Verfügung stehenden Spot 5 Satellitenbilddaten anhand eines objektbasierten Zuganges zu klassifizieren. Die Daten verfügen über eine Auflösung von 2,5 Meter im panchromatischen und 10 Meter im multispektralen Bereich. Ein Fernerkundungsbild besteht aus Zeilen und Spalten von Pixeln, welche die kleinste Einheit eines Bildes repräsentieren. Diese Pixel werden durch die Anwendung einer Segmentierung in sogenannte Segmente oder Bildobjekte zusammengefasst. Benachbarte Pixel werden aufgrund von ähnlichen Eigenschaften in Bezug auf Farbe und Form gruppiert. Nach diesem Arbeitsschritt ist das gesamte Satellitenbild in Segmente gegliedert. Diese unterscheiden sich in Bezug auf Farbe, Form, Größe und Textur. Des Weiteren können mit Hilfe dieser Software auch Nachbarschaftsbeziehungen zwischen den Segmenten betrachtet werden.

Im Untersuchungsgebiet von Singapur treten die Klassen „forest land“, „cropland“, „wetland“, „settlement“ und „no data“ auf. Ziel ist es, mit Hilfe der objektbasierten Klassifikation eine flächendeckende Landbedeckungsklassifikation zu generieren und davon die Landnutzung für Singapur abzuleiten. Die Klassifikation selbst wurde mit Hilfe von Regeln, basierend auf Schwellwerten und Nachbarschaftsbeziehungen durchgeführt.

Das erzielte Ergebnis wurde dann mit Hilfe eines „Accuracy Assessments“ evaluiert. Dazu wurden sogenannte „Random Points“ auf Basis der Klassifikation erstellt. Jeder dieser „Random Points“ liegt auf einem Segment und die Klasseninformation dieses Segments wird diesem „Random Point“ zugewiesen. Der nächste Schritt ist die visuelle Interpretation der Daten. Die Punkte werden mit ihrer Position in der „Basemap“, die von der Software „ArcMap“ zur Verfügung gestellt wird, verglichen. Diese „Basemap“ setzt sich aus Satellitenbildern sowie aus Luftbildern zusammen. Für jeden Punkt wird erneut die Klasse, der er zugehört, erhoben und gespeichert. In einer „Error Matrix“ werden die „Random Points“ eingetragen. Die Matrix vergleicht die Klasse der Punkte in der Klassifikation mit ihrer Position in der „ArcMap Basemap“. Mit Hilfe der Matrix wird eine „producer“, „user“ und eine „overall accuracy“ errechnet. Diese Genauigkeiten geben einen Aufschluss über die Güte des Ergebnisses.

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1. Introduction

The aim of this master's thesis is to develop a land use map of Singapore based on an object based classification approach. Object based image analysis (OBIA) developed amongst others through an increasing number of high resolution satellite image data and the growing awareness that pixel based methods do not suffice. The goal of OBIA is to establish a computer based image interpretation that is similar to the image interpretation of the human brain. The image objects that resemble the division of a landscape are similar to the way the human brain analyses a landscape. (CASTILLA, G., HAY, G.J. 2006)

The "Definiens Developer 7" software is used to classify the available satellite image data according to the land use. The land use classes are based on the IPCC top-level classes: "forestland", "grassland", "cropland", "wetland", "settlement" and "other land". Additionally, the class "no data" was included. These classes were defined in the "Good Practice Guidance for Land Use, Land-Use Change and Forestry" report of 2003, and they were adopted for the classification approach in the project. (IPCC 2003)

Understanding the difference between the terms land use and land cover is highly important, because they appear similar and are therefore often confused with one another. Within the practical work of the master's thesis the satellite data was primarily classified with regard to land cover. The land use classification was derived from the land cover information.

Land cover information is extracted from satellite imagery and aerial images. In this connection, the spectral and shape information is of prime importance. A land cover classification describes the observed outer biological coverage of the earth for example vegetation (natural or planted) or facilities which are constructed by people. Land cover classes in the practical work are for example "forest land" and "wetland". Land use, on the contrary deals with the effects and activities done by humans to a specific land cover type. Examples for land use classes in the practical work are "sealed area", "treeless area within sealed area" or "tree covered area within sealed area". (IPCC 2003)

Hence land use mapping focuses on the meaning of the surface of the earth for humans. In remote sensing two possibilities exist to determine the land use of an area. First, is the visual data interpretation and second the automated land use classification. The basis of a land use classification is a classification key, which depends on the task and the given data. Especially important are the spatial and the temporal resolution of the data and the number of available spectral layers. (GEODZ 2010)

1.1.Background

The Republic of Singapore aims to estimate the carbon stock for the entire area of Singapore according to IPCC Tier 3, which is the most detailed accuracy level. The following listing shows the goals of the project:

- *“Establishing a system of a national carbon monitoring for vegetation and land use,*
- *Annual data acquisition through a five-year period as part carbon monitoring (changes in carbon stock from year to year may be taken as the equivalent of emissions and absorptions),*
- *Collection of data from permanent plots in various land use categories, and from the various carbon pools in each category and*
- *Building up of capabilities and knowledge in relation to the management of assessing, estimating and reporting greenhouse gas emissions and removals from the LULUCF sector in agencies through appropriate training.”* (ANRICA et al. 2013)

An important issue of the project is to increase knowledge about the handling of emissions of heat-trapping gases derived from vegetation and land use. Another goal is to establish a historic monitoring of land cover and land use changes between 1989 and 2013. Among others high resolution Spot 5 and Landsat data was employed. Each of the given remote sensing images were segmented into image objects and an object based classification approach was applied to the data. Additionally, a change detection is applied to the data and the results are visually corrected. The purpose was to establish land cover maps with regard to the IPCC land cover classes for each year and maps that represent changes between the years. The baseline data comes from the year 2013. The remote sensing data was mapped with regard to the IPCC guidelines and land use classes. The results of the land cover and land use were derived from the segmentation of the remote sensing images, followed by a classification and change detection method. (ANRICA et al. 2013)

The objective of this master’s thesis is the development of a Singapore wide land use map with an object based classification approach. The IPCC guidelines and land use classes are also valid for the master’s thesis.

1.1.1. Carbon Budget

"A carbon budget can be defined as a tolerable quantity of greenhouse gas emissions that can be emitted in total over a specific time." (WWF 2012) Emissions of heat-trapping gases lead to rising temperatures and climate change. To avoid climate change, the global community has to limit its global carbon budget. Maintaining emissions within a certain limit is of upmost importance. The carbon budget is global because the emissions from every nation affect one share atmosphere or the "global commons". (WWF 2012) The latest report from the "Global Carbon Project" stated that the global community cannot emit more than 1200 Gt CO_2 in the near future. If current emission rates continue, this carbon budget will be consumed within the next 30 years. In the year 2014, 65 percent more CO_2 will have been emitted than in 1990, the year when the "Kyoto Protocol" was established. The largest emitters of CO_2, China, USA, EU and India are responsible for about 58 percent of these emissions. (FUTURE EARTH 2014) CO_2 emissions result from the burning of oil, gas or coal and as a result of the change in land use. The conversion of forests to pastures and croplands contributes to the emissions to a large extent. (GLOBAL CARBON PROJECT 2014)

1.1.2. REDD

"The acronym REDD stands for Reducing Emissions from Deforestation and Forest Degradation and the role of conversation, sustainable management of forests and enhancement of forest carbon stocks in developing countries". (THE REDD DESK 2014)

The aim is to decrease the emissions that occur due to deforestation and degradation of forests. The protection of forests is important as well as the sustainable cultivation of forests and the development of carbon storage in developing countries. (THE REDD DESK 2014)

Deforestation and degradation contribute 15% annually to global greenhouse gas emissions. This fact represents that the logging of forest releases more CO_2 into the atmosphere than the global transport sector. Therefore REDD+ was established by the United Nations. It aimed to compute the amount of carbon stored in forests, and give incentive to developing countries to halt deforestation. REDD+ provided founding to developing countries as a reward for stopping deforestation. (CODE REDD 2012)

REDD was founded in 2005. REDD+ emerged, when reducing the emissions produced by deforestation and forest degradation, sustainable management of forests and enhancing forest carbon stocks became important. The concept of REDD+ coincided with the goals of the

UNFCCC (United Nations Framework Convention on Climate Change). In the year 2013 the technical concept of REDD+ was concluded. One of the problems with REDD+ is, that no internationally binding agreement on climate change exists, and it was therefore not clear where the funding for the developing countries would come from. At first, money was provided by public funds, but the costs of REDD+ projects exceeded the available funding from more than 70 countries, who partnered with REDD+. (EUROPEAN FOREST INSTITUTE 2014)

The tasks of REDD+ include:

- *Reducing emissions from deforestation,*
- *Reducing emissions from forest degradation,*
- *Conversation of forest carbon stocks,*
- *Sustainable management of forests,*
- *Enhancement of forest carbon stocks.* (The REDD Desk 2014)

An area of four billion hectares all over the world is covered by forests. This area represents 31% of the land surface itself. However, forests are decreasing. From 1990 to 2000 an estimated 8.3 million hectares disappeared per year. Until 2010, the loss of forests per year declined to approximately 6.2 million hectares. Tropical regions are hit the hardest by the loss of forests because deforestation leads among others to biodiversity problems. Forest degradation results in the release of carbon dioxide into the atmosphere, which contributes to the greenhouse effect. Forests serve as a carbon stock and therefore act as carbon sinks. When forests are destroyed the stored CO_2 is emitted back into the atmosphere as a heat trapping gas. Carbon dioxide is caused by anthropogenic emissions. About 10% of the total global carbon budget is caused by the conversion of forest areas into “other land”. Preventing deforestation is therefore an essential measure to preventing climate change. Deforestation mainly occurs due to the rising demand for food, fuel and forest products. Reasons for deforestation include agriculture, timber extraction and urban and infrastructure expansion. In tropical regions the causes of deforestation vary. In Latin America for example agriculture and logging are significant causes of deforestation, whereas in Asia cultivation of palm oil, coconut, rubber, teak and timber plantations are among the main causes of deforestation. (THE REDD DESK 2014)

1.2. Objectives

The goal of this master's thesis is to classify Singapore according to the IPCC top level classes. The given Spot 5 satellite data is classified using an object based classification approach. The basis for this classification is the segmentation of the given satellite image. Pixels are therefore merged into image objects, also referred to as segments based on a specific segmentation algorithm. The resulting image objects differ with regard to color, shape, size and texture. These characteristics were essential for the land use mapping.

The satellite data was classified based on a user defined rule set. Thresholds and neighborhood relationships were primarily used to classify the land cover of the satellite image data. The land use was derived from the land cover classification based on rules concerning size, due to a given minimum mapping unit (MMU) and the neighborhood relationships.

An expected problem within the classification is the size of the satellite image, because the software is not able to edit large satellite images. Furthermore the atmospheric influences, different types of forests, dried up grassland and similar class types play a major role in the classification process.

Due to the problem of the size of the data, the whole image was split up in several images.

The errors that may occur because of the spectral similarities can be solved with a visual correction to detect and correct incorrectly classified image objects. The affected image objects are then assigned to the proper class.

Concluding the classification result of the "Definiens Developer" is compared to the result of the "Impact" software. "Impact" is a software used at Joanneum Research. Both classification methods used the same data. The difference is that the "Impact" software combined an ISODATA pixel based classification method with an object based classification method. The land cover was classified with the ISODATA approach and the land use with the object based approach.

1.3. Structure

The chapter after the introduction presents current state of the art technology discussed in emerging research and projects. Primarily, projects are introduced that focus on the object based analysis per se. Then, literature focusing on the object based land use classification within urban areas are discussed, followed by literature concerning pixel based classification approaches Additionally, pixel based land use classification approaches are introduced and finally studies that compare pixel and object based classification approaches are described. In these studies an attempt is made to argue how these methods differ from each other.

In the third chapter the investigation area itself is described with regard to area, geographic conditions and demography. Then information about the SPOT 5 satellite is provided. The reader receives information on the resolution of the satellite image data, the available image layers etc... In addition, the third chapter deals with the software used for the data preprocessing, the classification itself and the calculation of the accuracy to evaluate the quality of the classification result.

The fourth chapter discusses the nomenclature. Primarily the IPCC land use classes are and their adaption for the Singapore project are explained to the reader. The chapter closes with the definition of the term minimum mapping unit (MMU)

Chapter five focusses on the methodology. The different classification approaches and the visual interpretation are discussed as well as the applied methods within the “Definiens Developer” and “ArcMap”.

The sixth chapter deals with the theoretical and practical workflow. The theoretical workflow discusses the most important steps from the segmentation to the classification and the visual correction to the accuracy assessment. The practical workflow describes the actual steps that were applied in the classification process.

In the subchapters of chapter 7 the results of the accuracy assessment of the “Definiens Developer” are compared to the results of the “Impact” software. Concluding subsets of the original images are compared to subsets of the classification results.

The eighth and last chapter includes a conclusion, which focuses on the benefits of an executed object based classification approach and attempts to provide further perspective should this approach be appropriate for a land use mapping based on Spot 5 satellite image data.

2. State of the art

This chapter describes the state of the art technologies emerging in research, concerning the object based classification, land use projects within cities and common land use classification techniques.

2.1. Object based image analysis

Thomas Blaschke's publications regarding object based image analysis contribute to the theoretical background of this master's thesis. He wrote many articles on this topic himself and contributed to many papers. In the article "Object based image analysis for remote sensing" from 2009, he stated that the rising number of commercial high resolution data leads to the development of an object based image analysis (OBIA). The aim of the applied segmentation process is to create image objects formed by grouped pixels, which are homogenous and do not overlap one another. The scale is of upmost importance, because different image data requires different scales. Sometimes similar objects of the same image need a different scale. The main objective of the object based image analysis is to prohibit the appearance of the so called "salt and pepper effect". (BLASCHKE 2009) BLASCHKE, T. AND STROBL, J. (2001) published the article "What's wrong with pixels?" in which they analyzed why a classification based on pixels is not satisfying when dealing with VHR data. They stated that the problem of pixel based classification is that no shape information is integrated into the classification. They argued that the neighborhood relationship is especially important for high resolution data, because nearby pixels belong, with a high probability, to the same class. Additionally, they indicated that an object based classification can use the textural characteristics of pixels as well as the spectral and the shape. An often encountered problem is the segmentation of the image, because a high number of algorithms implicate many possible solutions. The segmentation of an image is the basis for its classification. Another problem are the land use borders, because in nature the transition between land use forms is more often fluid than strict. In this case, it is difficult to create meaningful image objects automatically. The applied scale plays an important role within the segmentation, but object based classification provides a greater advantage because it groups pixels into image objects, which include more information than a single pixel. The spatial information is also of major importance. (BLASCHKE, T. AND STROBL, J. 2001)

2.2. Object based classification examples

The "eCognition" software and its successors are a very powerful instrument for an object based classification approach. The following passages discuss research used in the software for a classification of urban areas.

TAUBENBÖCK, H. et al. (2006) published an article about an urban classification of Istanbul based on IKONOS data using a multispectral resolution of four meters and a panchromatic resolution of one meter. The basis for the classification was the execution of a multiresolution segmentation. The applied classification was based on a rule set that used shape values and neighborhood features to classify the image objects. The NDVI was the only spectral value used in this study. With the help of the NDVI a vegetation mask was produced. The shape features length and length to width were used to detect segments which represent the class roads. Problems occurred due to shadows and curved street segments. Land cover classes like houses were also classified with the help of shape parameters and neighborhood relationships. The accuracy assessment states an average accuracy of more than 82%.

Another approach for an object oriented classification method is given by GRIFFITH, J. (2005). The land use of city of San Antonio was classified based on orthophotos of the years 1995, 2000, 2003 and 2004. Additionally a Landsat ETM+ scene was used. The Landsat image was loaded into the "eCognition" software and a subset of this image was created. This subset included water bodies, agricultural areas, rural areas, buildings and roads. A multiresolution segmentation was applied to the data, with a scale parameter of 20, a shape parameter of 0.3 and a color parameter of 0.7. The compactness and smoothness were set to 0.5. A nearest neighbor classification was conducted on the data, thereby selecting training areas. Selecting an adequate number of samples per class was therefore necessary. The whole image was classified based on these training samples. An accuracy assessment was executed to estimate the accuracy of the classification result. The confusion matrix showed an overall accuracy of 100 percent.

REVESHTY, M. AND RABET, A. (2012) classified the land use of Zanjan city based on an object oriented approach. Contrary to GRIFFITH, J. (2005), in this study high resolution Quick-Bird data with a spatial resolution of 0.6 m was used. In this study all three bands of the Quick-Bird imagery are weighted equally. The scale parameter was set to 30, the color to 0.5, shape to 0.2, smoothness to 0.4 and compactness values to 0.5. The classification was also executed with the help of the nearest neighbor approach. Furthermore the brightness and geometry values were used for the classification. Within this area ten classes occurred. An accuracy assessment was applied to the classification result. The classes green space, dense trees, Buildings, footprint bodies and agricultural lands achieved a high accuracy. The accuracy of the class roads was low, because of their similarities to other classes. The resulting overall accuracy was 81%. This represents a relatively high accuracy percentage and is considered an adequate result.

In an article by MHANGARA, P. et al. (2011) the land use of the investigation area of Cape Town in South Africa was determined. They used multiresolution aerial photographs to classify the area. Again a multiresolution segmentation was applied to the data and all four image layers were equally weighted. The shape parameter was weighted 0.3 and therefore the color criterion was 0.7, the compactness and smoothness were set to 0.5. The threshold definition had a major influence on an adequate classification. In this study "SEaTH", a feature analysis tool was additionally used for classification in "eCognition". This feature helps the user to define an optimum threshold which allows the user to find the best possibility for separation between two classes. The classification was based on spectral values, and geometric features. The NDVI (Normalized Differenced Vegetation Index) and the NDWI (Normalized Differenced Water Index) were additionally calculated as spectral values. They evaluated the accuracy of the classification using reference data and random points which were calculated with the help of the pan sharpened image. The additional use of the "SEaTH" feature was important for the statistical analysis of the segments. The object oriented classification approach reached an overall accuracy of 93.2%. The user and the producer accuracy were also significantly high for each class. Classification problems derived due to similar spectral values of segments belonging to the bare area class or building class. Had a digital surface model been used, these problems could have been avoided.

HEROLD, M. AND SCEPAN J. (2002) used the "eCognition" software to apply an object oriented classification on the area of Santa Barbara in California. The land cover and land use was classified based on IKONOS data. In this study the spectral layers were weighted equally. The scale parameter was set to 8, to detect smaller features within the images such as houses, pools or single trees. Additionally the shape parameter was set to 0.3 and therefore the color criterion had a value of 0.7. The smoothness criterion was set to 0.4 and the compactness to 0.6. The segments in the image were classified with the help of their spectral and spatial features. Fuzzy class descriptors were defined by the users. A nearest neighbor classification process was used in addition to assign the image object to a specific class. They established three levels to classify the IKONOS dataset. These levels were hierarchically structured, the first level included the four main classes, and second the second and third levels contained the sub-classes. Within level one the spectral information was used to separate between the different classes. Additionally, level two used shape values to distinguish between the classes. In level three the spectral image object information was used. The executed accuracy assessment showed that water bodies had a significantly high classification accuracy as well as green vegetation or swimming pools. Dark roof tops and roads exhibited the lowest accuracy due to the fact that they have similar spectral values. An overall accuracy of 79% was reached and considered as an adequate result.

ZHU, X. et al. (2004) classified the land use of Beijing City based on remote sensing Spot data of different years. Spectral, shape, context information and mutual relationships were considered for the classification in the "Definiens eCognition". The scale parameter was set to 100. The classification started with the class "water area". Then the NDVI was defined to classify vegetated areas. The vegetated areas were distinguished with the texture information. The shape information was used to differ between the classes other objects, urban construction land, rural land and other construction land.

DARWISH, A. et al. (2003) published a study of an urban land cover classification of the city Algiers in Algeria. For the classification two types of image data were considered: an IRS-LISS image that offers a spatial resolution of 20, and three spectral bands and a Landsat TM image with a spatial resolution of 30 meters and six spectral bands. Additionally ground truth data was constructed. Then, five main classes with 11 subclasses were defined.

The software "Erdas Imagine" was used for classification. Examples for each class were determined and used for the classification of the whole image. The minimum distance and the maximum likelihood method were applied on the resulting classification. The data was further processed within the "eCognition" software. The segmentation of the image was done hierarchically, 3 different levels were applied. The levels offered different scale parameters. The level 2 segmentation was executed with a scale parameter of 8, a color criterion of 0.6 and a shape criterion of 0.4. The shape criterion was a combination of smoothness and compactness. This level was used to classify linear segments like streets or rivers. Level 1 included a finer segmentation and level 3 was built up to extract areal objects. Level 3 had a scale parameter of 25 but the other parameters were the same as in level 2. (DARWISH, A. et al. 2003)

Each satellite image was classified using the minimum distance method and the maximum likelihood method, together with training areas and the object based classification method. The resulting classifications were compared. An error matrix and the Kappa value were defined. The results of the accuracy assessment show that the minimum distance method led to better results than the maximum likelihood method. For the 11 classes the object based method was better than the maximum likelihood approach, but considering the 5 main classes, the MLC was better than the object based method. If the Landsat TM image and the IRS image were to be compared, the results would be highly similar, because of the fact that both images have advantages and disadvantages. Landsat offered a better spectral resolution and IRS a better spatial resolution. Concerning the object based classification result, the IRS image had slightly better results. (DARWISH, A. et al. 2003)

2.3. Pixel based classification examples

In the article published by Wijnant, J. and Steenberhen T. (2004) the southeastern area of Brussels was investigated with the help of Ikonos satellite image data. The remote sensing data of the year 2001 offered a resolution of 1x1 meter in the panchromatic band, in contrast to the 4x4 resolution of the four given multispectral bands. The investigation area includes different land use types. A dense built-up area is gives as well as green areas or avenues. Additional data like a base map with information about streets or buildings was given as well as the Corine Land Cover Map. The Corine data served as a reference for the accuracy assessment.
The given Ikonos data was preprocessed, geometric and spectral corrections were necessary. With the help of an unsupervised classification method and human interpretation the land cover signatures were defined. This unsupervised classification approach was executed on a subset of Brussels and achieved 30 different classes. These classes were further regarded. Some of them were merged based on a visual interpretation. Finally 12 classes were used for the classification. The occurring “salt and pepper” effect was reduced with the help of a majority filter within the “Erdas Imagine” software. Next, the supervised maximum likelihood classification was executed on the data. Due to the fact that the land cover classification is the basis for the following land use classification, the quality of the

classification result is essential. The land use classification required the determination of land cover parameters. These parameters were used to distinguish between the different classes. For example the parameter total area per land cover class was calculated for the existing pixels. Finally five land use classes were defined. The accuracy assessment was with 73% rather low. The producer's accuracy was very similar in the different classes whereas the user's accuracies were quite different. The classes that concerned the built area showed lower accuracies than those that concerned parks and forests. (WIJNANT, J. AND STEENBERHEN T. 2004)

In the study of Hester, D.B. et al (2008) the area of Raleigh in North Carolina was investigated. The investigation area offers urban and suburban land as well as forest and wetlands. This study was released to with regard to an investigation concerning the land cover change within the Raleigh area. For the classification panchromatic and the multispectral QuickBird data were used. The panchromatic and multispectral satellite images were combined to improve the resolution. After the combination the ground resolution of the data was 0.61 meters. These preprocessing steps were done with the "Erdas Imagine" software. The satellite image data was classified with the help of supervised and unsupervised classification techniques. Six land cover classes were defined in the study. Primarily a maximum likelihood approach, a supervised classification method, was applied on the data. Therefore 25 classes were used. This approach led to 138 training areas within the satellite image. The result of the supervised classification was combined into the six land cover classes based on a visual interpretation. An unsupervised ISODATA classification method was applied on this result to gain a new outcome. Next, a majority filter was applied on this classification result to reduce the resulting "salt and pepper" effect. These filters are necessary to eliminate areas that are smaller than the defined minimum mapping unit (MMU). An accuracy assessment was done to evaluate the quality of the classification result. On the one hand the random point technique was applied. In this case random points were created for the classification result. These were then compared to the reference data. The resulting overall accuracy was 83.0 percent. To improve the result, the ArcGIS was used to minimize the errors that occurred in the class water. An overlay for the class water was developed. Then an unsupervised classification was applied on the classification of the class water. Next, the same classification steps were applied on the data as in the beginning. The overall accuracy increased to 89.3 percent.

The study of Al-doski J. et al (2013) discusses the monitoring of land cover changes in Halabja City. The investigation area is located in the northeast of Iraq. Landsat TM data of the year 1986 and 1990 was used for the study. To avoid difficulties, the two images were recorded with the same sensor and at nearly the same time. The data needed to be preprocessed. A radiometric normalization was done due to the fact that the image data was influenced by solar illuminations, atmospheric scattering and absorption. Additionally reference data is given in terms of historical images. The reference data played a major role within the classification and the accuracy assessment.
The K-means algorithm was used for the determination of the classes. The pixels of the image were assigned to a class with the help of the available bands. The occurring number of classes was influenced by the defined number of cluster centers. The maximum likelihood classifier (MLC) was applied on the data. The MLC assumes that the class members are normally distributed.
The software's ENVI 4.8 and ArcGIS 9.3 were used for the production of thematic maps and the analysis of the land cover changes. The given data was classified with the k-means and the maximum likelihood method separately. But these approaches showed a very poor accuracy quality. Therefore these two methods were combined. This new access disposes three steps. Primary the k-means method was used to generate forty different clusters. These clusters were then labelled. The forty clusters were therefore assigned to five land cover classes. These five classes were then used in the last step. The spectral signatures were applied within the supervised classification. The supervised MLC method was applied on the data. The quality of the results was improved with the help of a visual interpretation.

The accuracy was calculated with a "confusion matrix". The given reference data is important for the calculation of the accuracy. It was necessary to create sample points that represent the different classes of the classification result and to compare them with the reference data. The points were then registered in the matrix. The values in the diagonal of the matrix represent the correctly classified points. The overall accuracy of the year 1986 the compared classification was 92.2 percent, whereas the individual k-means classification accuracy was only 68.8 percent and the MLC Classification only 62.8 percent. The accuracies for the year 1990 were 96.8 percent within the compared classification and 86.6 percent with the help of the k-means classification and 68.2 percent in the MLC classification. (AL-DOSKI J. et al 2013)

2.4. Pixel based vs. object based land use classification techniques

The following studies relate to common land use classification techniques. In the majority of the cases a comparison of the classification results of the pixel and object based approach was made. Both methods offer supervised and unsupervised approaches. Whereas the pixel based classification processes were executed with the “Erdas Imagine” software, the object based classification methods were applied with “eCgonition” or a successor software such as the “Definiens Developer”.

ORUC, M. et al. (2004) published a study where the area of Zonguldak in Turkey was classified with Landsat 7 ETM data, which offers six spectral bands. The pixel based method executed an unsupervised classification at first, followed by a supervised classification method. The study applied three different pixel based methods, the minimum-distance, maximum likelihood and parallelepiped method. Primarily, they used ISODATA (Iterative Self-Organizing Data Analysis Technique) to detect spectral clusters to obtain previous knowledge about the study area. With the help of ground truth data, clusters were formed. In the end seven classes were established and used as training areas for the investigation area. Then a supervised classification processes was applied. These methods were built on the training areas and given reference material. Each method used the same training areas and coloring for a better comparison between them. During the object based approach a segmentation was executed on three levels based on the “eCognition” software. The first level had a scale parameter of 5, a shape parameter of 0.3 and color parameter of 0.7. The compactness value was set to 0.1 and therefore the smoothness exhibits a value of 0.9. Level two had a scale parameter of 10, a color and shape parameter of each 0.5 as well as the smoothness and compactness. The third level had a scale parameter of 1 and therefore the shape is 0 and not considered, smoothness and compactness have values 0.5. That results showed that the highest scale parameter was the best to classify the data. A random choice of 350 pixels within the investigation area was defined for the accuracy assessment. The accuracy was measured by comparing the pixels with the reference data. An error matrix was created, which shows the producer’s and the user’s accuracy. The maximum likelihood approach showed the best accuracy according to the pixel based approach. In general the object oriented classification approach reached the highest accuracies. The overall accuracy of the object based classification was much better than for all pixel based approaches. A reason for this could be the complexity of the segments.

Another example of a comparison between these two methods is presented in AVCI, Z.D. ET AL. (2011). In this study the pixel based ISODATA and maximum likelihood classification method and the object oriented classification method were applied. This study was executed based on multispectral Spot 5 data with a spatial resolution of 10 meters and 4 spectral bands. During the unsupervised pixel based classification approach the pixels were clustered into spectral classes. When the user applied the supervised method, training samples of the classes were defined. 100 classes were defined and 10 iterations were run. 100 spectral clusters resulted and were combined into six land cover types. One of these types was a mixture of urban with vegetation. The supervised maximum likelihood classifier was applied on eight different classes. In the object based approach the segmentation was executed on three levels also based on the "Definiens Professional". The scale parameters for these levels were 200, 60 and 10. They used the same composition of the homogeneity criterion for all levels. The shape was set to 0.3 and therefore the influence of the color criteria was weighted 0.7. The smoothness and compactness criteria were each weighted with 0.5. The classification was based on rules for brightness, length/width, the GLCM Homogeneity, and the maximum difference. The supervised object oriented classification was based on the same segmentation parameters. Therefore training areas were detected and a nearest neighbor classification was used to classify the image. Three methods were used to evaluate the accuracy of the classification. Primarily the classification results were compared to the ground truth data. Then they compared the histograms of the classification results. The third method was a visual analysis of the results. The ISODATA approach reached an overall accuracy of 75%, the maximum likelihood reached 82%, the object oriented condition based approach reached 88%, and the nearest neighbor alternative reached 85%.

The study of WHITESIDE, T. AND AHMAD, W. (2005) observed the Florence Creek area in Lichtfield National Park in Northern Australia. They used ASTER data with 14 spectral bands which can be divided in three visible and near infrared bands, six bands in the shortwave infrared and five bands in thermal infrared. Two scale levels were used for the segmentation of the image during the object oriented process. During the classification process, they selected samples for each of the defined land cover class. The editors assigned the resulting image objects to the classes with the help of their spectral, shape and contextual features. A maximum likelihood approach was applied as pixel based supervised classification algorithm. Therefore several training areas per class were recorded.

An accuracy assessment was executed for all applied methods. The overall accuracy for the object based approach was with 78% much better than the pixel based approach with 69.1%. Also the producer's and user's accuracy of the object oriented classification method were better.

CHEN, M. et al. (2009) used SPOT 5 data to apply an pixel-based and an object-based classification approach to investigate the area of Liangxaing Town in the Fangshan District in Beijing in China. Furthermore a DEM from the year 2004 and additional provided a help for the classification. The Spot 5 data offers the green, red and NIR band. The data was processed with the help of the "Definiens Developer" software.

Five land use classes were defined for the classification. Additionally, to the spectral bands, the NDVI was calculated. This feature was important for the classification of vegetated and not vegetated land. Water segments were classified primarily with the help of the red and the NIR band. Afterwards the NDVI was applied to classify the remaining pixels into vegetated and bare soil. In conclusion, the remaining pixels were classified with the help of the green band. The DEM was included and helped to differ between woodland and farmland. The maximum likelihood approach was applied as supervised classification method. Especially important for this approach was the spectral information. A problem in this method was that only the spectral information was considered, and the texture and context were disregarded. Based on the segmentation the image objects in the satellite image were assigned to a defined class according to particular rules and criterions. Their spectral, shape, size and context characteristics were used for the classification of the image. The segments were assigned to the class according to the defined criterions. Two working levels were defined and the spectral layers were weighted equally. The level 1 segments were the super-objects and contained the water body and woodland segments. The segments of layer 2 were the sub-objects and represented buildings and roads. The buildings and the roads were distinguished with the help of the length and the length/width features. (CHEN, M. et al. 2009)

An error matrix was calculated to evaluate the accuracy of the classification. The overall accuracy was proved greater in the object oriented approach than in the other methods. Additionally, the object oriented approach allowed the user to distinguish between roads and buildings with a relatively high accuracy. This was a problem in the pixel based approach because due to the similar spectral values and the fact no shape information on the pixels was available. The maximum likelihood classification method provided the worst classification accuracies. The major advantage of the object oriented approach was that spectral information and the spatial and context characteristics of an image objects were available. (CHEN, M. et al. 2009)

2.5.Summary

The object based classification methods offer a very good approach for the classification of a satellite image. Especially the “eCognition” and the “Definiens Developer” software were used for the object oriented classification. It is difficult or even not at all possible to transfer the rules and parameters etc. to other projects. Limiting factors are the scale parameter and the homogeneity criterion of a project, due to the fact that there are many combination possibilities. The scale parameter influences the size of the image objects. This value therefore depends on the task. The user has to try out many combinations to find an appropriate result. The studies within this chapter show, that in general there are similarities between the homogeneity criterions of the different articles. In the majority of the studies the shape parameter exhibits a low value of 0.2 or 0.3. Therefore, the color criterion has more influence on the building of the image objects. The smoothness and the compactness criterion are in the majority of the cases equal. Most pixel based approaches were executed with the “Erdas Imagine” software. Within the pixel based classification the unsupervised ISODATA and the supervised maximum likelihood and minimum distance methods were primarily used. The unsupervised methods were in many cases the basis for the supervised classification.

3. Study area, data and software

3.1. Study area

The city state Singapore, in Southeast Asia, is an independent republic. The country's capital located in the south of the main island is also called Singapore. The city is home a one of Southeast Asia's major harbors. The city-state ranges over an area of about 710 square kilometers, 573 square kilometers belong to the main island, and the remaining part is spread out over smaller islands offshore. In the north the main island of Singapore is separated from Malaysia by the "Johor Waterway" and in the South the "Waterway of Singapore" serves as the border to Indonesia. Due to a high rate of colonization, Singapore sets a high value on land reclamation. The city-state expands into the ocean with the help of filling operations. (GORUMA 2014)

Singapore is administratively structured in five "Community Development Council (CDC) Districts". These areas are called the Central Singapore District, the Northeast and the Northwest District and the Southeast and the Southwest District. These districts are administered by majors and councils who are further administratively structured into town councils. (ASIEN.NET 2014)

According to the statistical department of Singapore about 5.3 million people lived in Singapore in the year 2012. The inhabitants belong to different ethnic groups. 76.8 % are Chinese, 13.8 % are Malay, 7.9 % are Indian and 1.4 % belong to other groups. About 1.2 million people who live in Singapore are foreigners or alien employees. 16.5 % of the inhabitants are under 15 year old, 73.8 % of the people are between 15 and 64 years and only 9.7 % are older than 65 years. (WKO 2014) Singapore has four community languages, Chinese, English, Malayan and Tamil. The English language is used in business life and instructed in many schools. (GORUMA 2014)

Singapore characterizes as a flat landscape. The highest peak is the "Bukit Timah Hill" with approximately 164 meters. Singapore has no natural lakes, the longest river is called "Seletar" and ranges over a length of 15 kilometers. The "Singapore River" with a length of only 3.2 kilometers is the most well-known river, because it runs through the urban area of Singapore. However a complex net of small water bodies and man-made water reservoirs do exist, but they do not suffice to supply the inhabitants of Singapore with enough drinking water. Some drinking water still has to be imported (SINGAPUR-PORTAL 2014)

Singapore lays only 1 degree north of the equator. A tropical humid climate with minor seasonal movement is dominant in this region. The temperature ranges between 26 and 32 degrees Celsius. In the months between June and September, the monsoon season occurs in the south-east and between December and March, it occurs in the north-east. These periods are characterized by lower temperatures and rainfalls. (SINGAPUR.NET 2014)

3.2. Data

Spot 5 satellite data of the year 2014 was used for the land use classification of Singapore. The following paragraph deals with general information about the Spot 5 satellite.

In May 2002 the Spot 5 satellite was brought into the orbit with an Ariane 4 rocket. The satellite orbits the earth at a height of 822 kilometers and with an inclination of 98.7°. The inclination describes the angle of the satellite orbit with regard to the equatorial plane. A full circle around the earth takes 101.4 minutes and depends on the degree of the latitude. The same areas are detected every two or three days. The satellite records the earth with a swath width of 60x60 kilometers. Spot 5 images have five image bands available, the green, red, near infrared (NIR), mid-infrared (MIR) and panchromatic band. The spatial resolution of the panchromatic band is 5 meters, in the multispectral band 10 meters and 20 meters in the shortwave infrared. (SATELLITE IMAGING CORPORATION 2001-2014)

“Google” data images were additionally used as reference data, because of their high resolution. Additionally ground truth information of locally inspections was used for the classification. This reference data was very important for the final visual correction, because of the high accuracy of the data.

3.3. Software

3.3.1. Definiens Developer

The “Definiens Devloper” software is a tool for the object based classification approach of remote sensing data. The “Definiens eCognition” software was released in the beginning of the year 2000. The software was developed for the version “Professional 5”. Since the year 2003 the “Definiens Developer” has evolved together with the “Definiens eCognition™ Server”. Then, the “Definiens Professional” line was integrated into the “Definiens Developer” line. This allowed the user the full access to the features of the “Definiens

Enterprise Image Intelligence™ Suite". The software itself is a highly powerful instrument for the implementation of an object based image analysis. Remote sensing data is analyzed automatically. (TRIMBLE GEOSPATIAL IMAGING 2014)

In this master's thesis the version "Definiens Developer" 7 was applied on the given Spot 5 data. The entire object based image classification was processed within this software. The images were classified with a ruleset based on thresholds. The "Definiens Developer" is discussed more detailed in chapter 5.2.

3.3.2. ArcGIS

"ArcGIS" belongs to the US software producer ESRI (*Environmental Systems Research Institute*). "ArcGIS" is a software for the collection, organization, analysis, communication and distribution of geographic data. The software is used in education, institutions, enterprises, and media all over the world. The "ArcGIS" desktop can be divided into "ArcMap" and "ArcCatalog". "ArcGIS" helps to distribute geographic information with the aim that arbitrary users can access and use the data. Meanwhile the software is available in the version 10.2. The software can be used on a computer desktop, online, with smartphones and tablets and other mobile devices. The resulting maps, etc. can also be displayed on all of these devices. The software can be used to develop maps and geographic information, which can be distributed over the web. With the help of mobile devices it is possible to generate real time measurements. Simultaneously this data can be analyzed by specialists with computers. The resulting maps can be released for all users and are available for smartphones, tablets and desktops. The users can adopt these results with other data and generate new maps. (ESRI 1995-2014)

In addition "ArcGIS"offers following options:

- *"Create, share and use intelligent maps,*
- *Compile geographic information,*
- *Create and manage geographic databases,*
- *Solve problems with spatial analysis,*
- *Create map-based applications,*
- *Communicate and share information using the power of geography and visualization."* (ESRI 1995-2014)

Within the work of the master's thesis, the software was used for the calculation of the accuracy of the classification result. The working steps are discussed in the chapter 6.1.5 and 6.2.9.

3.3.3. Erdas Imagine

The image processing software "Erdas Imagine" is raster-based, and allows the user to process geospatial data, vector data, and other images. Additionally, high resolution data and LiDAR data can be processed. "Erdas Imagine" can be integrated for example in "ArcGIS," but also in other remote sensing applications. Furthermore, the generated files, in most cases .img, can be imported in other applications (DATAONE 2014).

The software offers a large set of tools, for example, it is possible to orthorectify, mosaic, reproject, classify, and interpret remote sensing data. With the help of this feature the user can analyze the given data, and edit the data in diverse formats. The data enables the user to generate results such as maps or 3D models (Technical Innovation and Professional Services 2012).

The "Erdas Imagine" software was used for the data preprocessing. A layer stack process was applied on the data to combine the four multispectral a resolution of 10 meters with and the panchromatic layer that offers a resolution of 5 meters, to a new image with five spectral layers. The combination of these layers lead to a better resolution of the image.

4. Nomenclature

4.1. IPCC land use categories

The IPCC offers six different land use categories, which can be understood as top level categories representing the landscape. These categories coincide with the IPCC guidelines and regulations of the Kyoto protocol. Each of these top level categories has several subclasses. With these classes, classification of all areas of the earth is possible. These categories can be adapted by the countries, which therefore create new definitions of these categories. But they need to refer to the internationally defined definitions.
The naming of these categories is a mixture of land cover and land use types. But for convenience the term land use class is used. (IPCC 2003)

"These classes were selected because they are:

- *Reasonably consistent with the IPCC Guidelines;*
- *Robust as a basis for carbon estimation;*
- *Reasonably mappable by remote sensing methods;*
- *Complete in that all land areas should be represented in one or another category."* (IPCC 2003)

The following top level land use classes are given within the "Good Practice Guidance for Land Use, Land-Use Change and Forestry":

- Forest land

This category contains all parts of the earth which are covered by forest, based on thresholds used to define forest category. Furthermore it can be separated into administered and non-administered areas. (IPCC 2003)

- Cropland

This category contains arable crop, tillage systems and agroforestry. In Singapore the class cropland is divided into annual and perennial crops, however temporary fallow land is also a subclass of this category. The term temporary fallow land describes areas that are set at rest for one or several years and are then cultivated again. (IPCC 2003)

- Grassland

This category deals with areas like meadowland or nature meadowland which are not classified as cropland. Leisure time areas also belong to this class. The definition of the threshold for the classification plays a critical role in this case, because spectral information enables forest land areas to be classified as grassland. Without human intervention .these areas will not exceed this threshold. (IPCC 2003)

- Wetland

The top level category wetland contains those areas totally covered by water, but also areas that are all year or parts of a year saturated by water. These can be divided into administered and non-administered areas. An example for an administered area would be a water reservoir, whereas natural lakes or rivers are non-administered. (IPCC 2003)

- Settlements

The top level category settlement focuses on developed land, human settlement of arbitrary size, and infrastructure such as streets, railways etc…, if they are not a sub class of another category. (IPCC 2003)

- Other land

This top level category contains areas covered by ice, stone and bare soil regions. Furthermore all areas that do not fit into another category belong to other land. (IPCC 2003)

It is necessary that the parts of a landscape are assigned to only one class. If a country adapts these categories it is essential to report the new definitions and the applied thresholds and parameter values. (IPCC 2003)

4.2.IPCC land use classes in the Singapore project

Within the Singapore project the IPCC land use classes were respectively subdivided into sub-classes in the following way:

- 100 Forest land
    - 110 Stocked
    - 140 Treeless area within forest land
    - 150 Infrastructure within forest land
- 200 Cropland
    - 210 Perennial Crops
    - 220 Annual crops
    - 230 Infrastructure within Cropland
    - 260 Single trees, tree groups smaller than 0,5 ha
- 300 Wetland
- 400 Settlement
    - 410 Sealed area
    - 421 Tree covered areas within sealed area
    - 422 Treeless area within sealed area
    - 430 Cased water body
- 500 Other land
- 600 No Data

- Forest land

In relation to the Singapore project, the IPCC categories were adjusted to the circumstances in the investigation area. The image objects of the class “forest land” have a minimum size of 0.5 hectare and a minimum width of 20 meters. A problem occurs for some of the “forest land” image objects, because in the city they are not actually “forest land”, in this case they belong to the class “Tree covered areas within settlement” which is a subclass of the top level class settlement. The size of this subclass image objects is limited, image objects of this class must not exceed a size of 5 ha otherwise it is classified as “forest land”. Applying this MMU sometimes image objects of the class “forest land” appear in urban area, although there are obviously no forests. These occur due to the fact that neighboring groups of trees and allies are merged to segments that are 5 hectares or larger. The wrongly classified image objects were reclassified during the visual correction of the data. (ANRICA 2014)

The Table 1 shows the IPCC land use class “forest land”, the second column lists the forest types that arise in Singapore and the third column declares how the class “forest land” is structured. The main class is “stocked forest areas”. “Treeless areas within forest land” is a sub class and includes all grassland areas that are totally surrounded by “forest land”. “Infrastructure within forest land” is also defined as a sub-class. This class includes image objects that are classified as buildings, roads, landings, huts and so on. However, the segments can only have an area less than one hectare, otherwise the image object is assigned to the class settlement.

Table 1: IPCC Class “Forest Land”. Source: Anrica 2014

IPCC Land-use Class	**Major forest types of Singapore**	**Sub-strata for carbon assessment**
Forest Land	Primary forest Lowland dipterocarp forest Coast hill dipterocarp forest Secondary forest Abandoned plantations (oil palm, coconut, rubber) and village areas Exotic species-dominated stands (Albizia, Acacia, Leucaena, Cecropia) Adinandra forest Swamp forests	Stocked forest areas (ranging from early regrowth to mature/primary stand conditions) Treeless areas within forest land (includes grassland with or without bushes) Infrastructure within forest land (buildings, huts, roads, landings etc.)
	Mangrove forest	Mangrove forests

- Cropland

The annual crops contain vegetables, ornamental plants and root crops. Examples of perennial crops in Singapore are trees or shrubs. Plantations composed of coffee, bananas, cocoa, rubber trees and herbaceous crops are also part of this category. The class cropland also includes solitaire trees and is mixed with parts of infrastructure like buildings and roads. (ANRICA 2014)

The table below shows the content of the adapted IPCC land use class “cropland”. The first column shows the official name of the IPCC land use class. The second column lists examples of perennial and annual crops. The class perennial crop contains mostly agricultural crops of trees and tree nurseries. The annual crops on the contrary include low crops within agriculture such as vegetables. The third column shows the nomenclature of the classes within this IPCC land use class. There are the “perennial crops”, “annual crops” and “infrastructure within cropland". The classification content of the first two classes was previously explained. The third class includes all infrastructures within cropland, such as houses, shades, roads, etc…

Table 2: IPCC Class "Cropland". Source Anrica 2014

IPCC Land-use Class	**Major vegetation/land-use types of Singapore's cropland**	**Sub-strata for carbon assessment**
Cropland	Perennial crops: Fruit trees and shrubs Tree nursery (ornamental and forest trees) Horticulture Annual crops: Plant nursery Vegetable farm	Perennial crops (sub-divided into: Fruit trees/shrubs Tree nursery Horticulture Annual crops (with or without solitaire trees) Infrastructure within cropland (non-cultivated) (buildings, shades, huts, roads, landings etc.)

- Grassland

The grassland category does not occur in the Singapore project as a top level category itself. However, it arises as a sub-level class in "forest land" and in "settlement". In this case, it belongs to forest land, if it is totally surrounded by forest, otherwise it is a part of settlement. (ANRICA 2014)

- Wetland

In the case of the investigated area all parts of Singapore, which are permanently covered by water, for example natural rivers or lakes would be part of this top level category. Also natural or semi natural water bodies and waterways, or canals, water reservoirs, and quarry ponds which are man-made belong to this category. (ANRICA 2014)

- Settlement

In the SINCA project the possibility exists that infrastructure occurs in forest land or cropland and hence is a subclass of them. However if the infrastructure exceeds the size of one hectare, it is classified as settlement. (ANRICA 2014)

Table 3 displays how the category settlement is composed in the Singapore project. The second column shows which subclasses occur within the main land use class “settlement”. There are vegetated areas, tree covered areas and sealed areas. The subclass vegetated areas include for example fields, sport fields, golf courses, roof gardens, gardens next to buildings et cetera. The tree covered areas include parks, avenues, single trees, etc.. The main condition for this class is that the tree covered area must not exceed an area of 5 hectares, otherwise it is assigned to the class “forest land”. The main class “sealed area” comprises all infrastructure image objects such as: buildings, roads, industrial sites, airports et cetera. Bare soil areas, sealed sports fields, cased ponds or swimming pools are additionally examples of the class “sealed area”. The third column includes the nomenclature of the classes in the classification approach. The classes “sealed area”, “tree-covered areas” and “other vegetated areas with or without solitaire trees” are used to classify the image object according to the IPCC top level class “settlement”.

Table 3: IPCC Class “Settlement”. Source Anrica 2014

IPCC Land-use Class	Major vegetation/land-use types of Singapore’s urban environment	Sub-strata for carbon assessment
Settlement	Vegetated areas: Streetscape (including park connectors) Fields/sports fields/school fields Golf courses (meadows with scattered hedges and trees Tree covered: park lands (including zoo, bird park; as far as not defined as “forest land”), Landscape gardens (on the premises of schools, factories, shopping centers, residential areas) Cemeteries Vegetation on sealed areas (roof gardens, vertical greenery)	Tree-covered areas Other vegetated areas with or without solitaire trees
	Sealed area (un-vegetated): Infrastructure and buildings (roads, industrial sites, harbours, airports) Bare soil, e.g. reclaimed land Sealed sports fields Cased ponds and swimming pools	Sealed areas (all areas without any vegetation, infrastructure like buildings, roads, landings etc.)

- Other land

After the visual correction of the data, image objects which did not fit into a category were assigned to this class.

- No Data

Parts of the satellite imagery are covered by clouds and their shadows. In this case a classification of these areas is not possible. Then affected segments are classified as no data segments.

4.3.Minimum Mapping Unit

With the help of a minimum mapping unit it is possible to determine a minimum size or dimension of a segment. It is declared at which size a feature is not considered any more. (WETLANDS-AT-RISK PROTECTION TOOL 2010)

In the practical work of the master's thesis, the minimum size of image objects is in general 2500 square meters. This MMU was adapted for the classes "forest land", "tree covered areas within sealed area" and "infrastructure within forest land". "Forest land" image objects need to have a general size of 0.5 hectares or larger and "infrastructure within forest land" must not be larger than 1 hectare. Image objects of the class "tree covered areas within sealed area" need to be 5 hectares or smaller, otherwise they would belong to the class "forest land". All image objects which do not achieve these conditions are reclassified.

5. Methods

5.1. Classification and visual interpretation

5.1.1. Classification

Classification is a method within the image processing, based on algorithms areas with the same characteristics are determined. These algorithms detect for example water, forest et cetera in remote sensing data. To classify a raster image, the sensors of the satellites must distinguish several spectral signatures. Depending on the classification method it is necessary to define training areas. The classification of remote sensing data often uses multiple color channels at the same time. With the help of the classification single pixels or groups of pixels are assigned to a class according to their spectral signature or shape parameters. The spectral signature depends on the reflection properties of the objects. Each class is characterized based on specific features, optimally the classes differ from one another. Each pixel is examined according to the characteristics of each class. A pixel is assigned to the class which describes it best. (LEXIKON DER FERNERKUNDUNG 2014a)

Classification can be executed by two methods. First, is an pixel based image analysis and second is a object based image analysis. Pixel based image analysis involves assigning the pixels of an image to a class according to their spectral characteristics. Features like the texture or neighborhood are irrelevant for the assignment to a class. Pixel based classification methods are limited when high resolution remote sensing data has to be classified. (LEXIKON DER FERNERKUNDUNG 2014b) The object based image analysis divides an image primarily into image objects, and then the pixels and their neighborhood are examined. This classification approach assumes that nearby pixels belong to the same class and will be merged. Furthermore, segments differ in spectral, shape, texture and context characteristics. (FIS 2014a) The greatest difference between the pixel and object based classification approach is the segmentation process, which is the basis for the object based classification approach. The segmentation process is a generalization of an image, and groups the pixels into image objects. Both classification approaches distinguish between supervised and unsupervised methods. (LEXIKON DER FERNERKUNDUNG 2014b)

The unsupervised classification technique assigns pixels according to their reflectance characteristics into clusters. The user must simply define the number of clusters and the bands that are used. Based on this information the clusters are created. Knowledge about the meaning of the classes is not necessary. Hence no training area data or other reference data is needed. Often this method is not used as an autonomous approach, but for the preparation of a supervised classification. The ISODATA method is an example of an unsupervised classification approach. (ALBERTZ, J. 2007) ISODATA stands for Self-Organizing Data Analysis Techniques. The user has to simply determine the number of classes within the image, and the computer automatically calculates which pixels belong to a class. This approach presupposes a regular distribution of the values of each spectral band and automatically sets the midpoints of a class. Then, the distance from each pixel to each pixel midpoint is calculated, and pixels with a minor distance are merged. This iterative process is then repeated again and again. Consistently the distances are measured, pixels are assigned to a class and the midpoints of the classes are calculated. This process stops if a specific number of repetitions are achieved. Another reason for a process breakup is the absence of pixels able to change their class. This irrespective classification approach does not depend on the user. This classification method is also not without problems. When the computer has no additional information besides the characteristics of the pixels, a separation of classes which normally belong together could occur. (FIS 2014b)

The supervised classification technique involves the user defining training areas for each occurring class in the remote sensing data. A training area is a certain part of an image that represents a sample of a class. Due to logical reasons only those areas should be taken as examples that are clearly belonging to a certain class. It is important to choose an adequate and representative number of samples for each class. The entire satellite image is classified based on the spectral signatures or characteristics of segments of the training data. Pixels can be assigned to a class amongst others with the help of the maximum likelihood or the minimum-distance classification method. The maximum likelihood method uses the mean value and co-variance matrix derived from the training area and the probability that the single pixels belong to one of these classes. The pixels are assigned to the class with the highest probability. The minimum distance approach on the other hand is a simple algorithm. Primarily, the mean values of the measurements are calculated in the single spectral values. The Euclidian distances of the pixel to be classified to the center of these classes are calculated for each pixel. Then, a pixel is assigned to the class with the nearest center. (ALBERTZ, J. 2007)

5.1.2. Visual image interpretation

The visual image interpretation process is a complex process. The accuracy of the interpretation result depends on the skills of the interpreter. The analysis of the data depends on the skills of the interpreter. The analysis includes the identification of diverse natural or man-made objects which consists of points, lines, or areas. The interpretation distinguishes between two working steps: the creation of objects polygons such as streets, buildings, etc., which depends on the experience and skill of the interpreter and the actual interpretation process. Within the interpretation process conclusions are drawn from identified objects. Conscious combination based on previous knowledge lies in the foreground. The shape, size, shadow, color, pattern, texture and context are for instance important elements in the visual image interpretation process. They help to identify landscapes elements from remote sensing data. (LEXIKON DER FERNERKUNDUNG 2014c)

5.2. Methods in "Definiens Developer"

The image analysis approach of the "Definiens Developer" software is similar to the one of the human brain, because when humans consider an area with their eyes, they observe the characteristics of the area. For example the characteristics such as size, shape, color et cetera of an area are noticed. Based on this information the human brain forms an object of the considered area. The "Definiens Developer" works in the same way, pixels are merged into image objects according to their characteristics. (DEFINIENS AG 2007a)

The "Definiens Developer" offers methods for the object oriented classification of images. An image consists of image layers and is built up on pixels. Different image layers include different information. The most well-known image layers are the red, green, blue and the near infrared layer. Additional information like geo information or metadata can also be included in the classification. The user must generate a project, which comprises all important information for the classification of an image. This software allows the user to add thematic layers to a project. An image analysis of a scene leads to the division of an image into several image objects, also referred to as segments. An image object is composed of pixels with similar spectral values and describes a particular area of an image. The neighborhood of an image plays also a major role. Each image object belongs to a class, the classes, and their names, and colors will be defined in the primarily working steps. (DEFINIENS AG 2007a)

An image can be divided into several image object levels, which together form an image object hierarchy. The following Figure 1 shows a hierarchical structure of an image. The basis of this image object hierarchy is the pixel level, from which the image object levels are built upon. However, an image object level can also be based on another image object level, and it is possible to duplicate a level. The "Definiens Developer" calculates the image objects in the pixel level or in an image object level. All processes and algorithms are done at a designated level, and it is important for the user to specify the layer that is being worked on. (DEFINIENS AG 2007a)

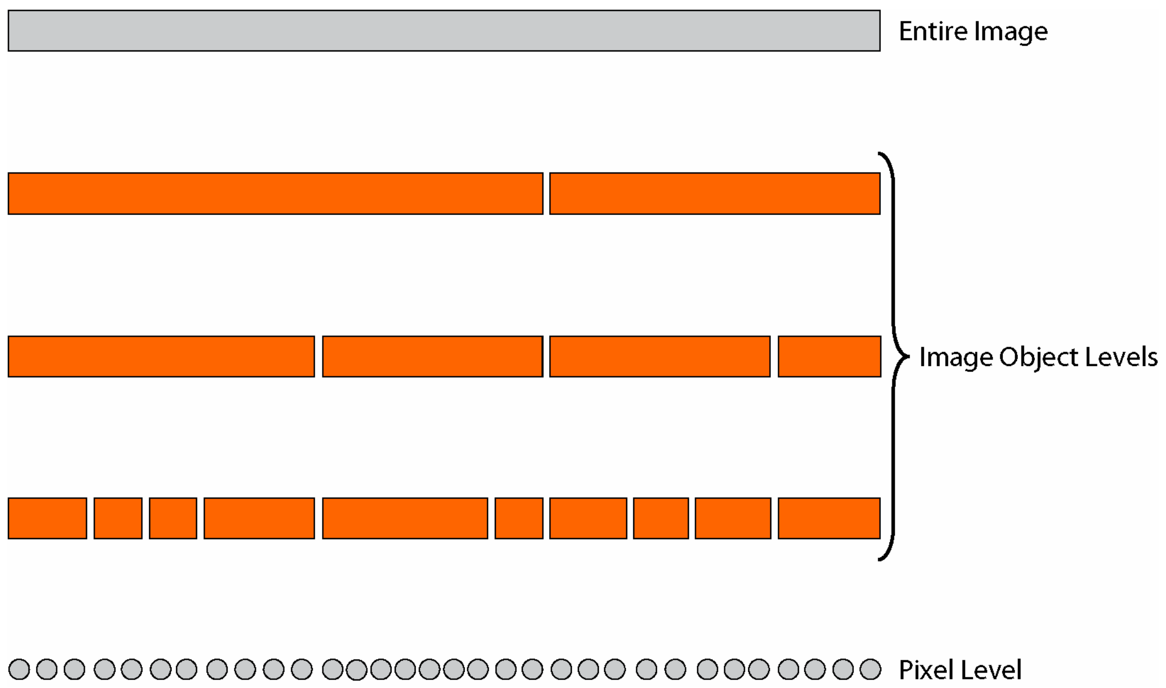


Figure 1: Image Object Hierarchy. Source: DEFINIENS AG 2007a.

The term feature, which is commonly used in "Definiens Developer", needs to be explained. A feature contains information about a particular object. This information can represent values, measurements or attached data. Two types of distinguishable features exist: On the one hand there are the image object features which describe the segments concerning the characteristics of a segment. On the other hand there are the global features, which do not concern a single segment, but all segments which contribute to a certain class. (DEFINIENS AG 2007a)

5.2.1. Segmentation algorithms

The first and most important step for classification in the "Definiens Developer" is the segmentation of an image. This process separates the pixels of an image into homogenous and non-overlapping image objects. Segmentation is done to sub-divide an image represented by the pixel level or an image object level into smaller image objects. Segmentation processes are used to construct new image object levels. The "Definiens Developer" software offers several segmentation algorithms for the user. (DEFINIENS AG 2007b)

These segmentation processes can be grouped into two main types of segmentation. On the one hand there is the top-down and on the other hand the bottom-up segmentation approach.

5.2.1.1. Top-down Segmentation

The top-down segmentation approach cuts existing objects into smaller image objects. The entire image can but must not be the basis for the algorithms. The chessboard segmentation and the quad tree based segmentation are well known examples of the top-down approach. (DEFINIENS DEVELOPER XD 2.0.4 – USER GUIDE 2012)

The Figure 2 gives the reader an idea how the top-down segmentation operates by cutting an image into smaller objects.

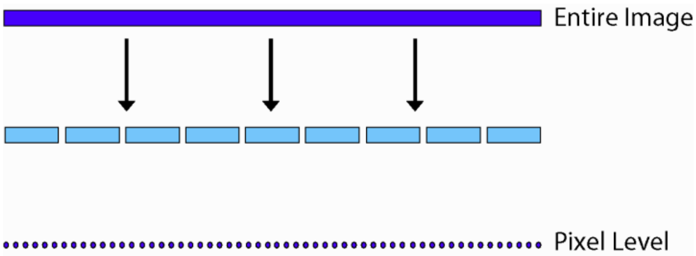


Figure 2: Top down segmentation approach. Source: DEFINIENS AG 2007a.

5.2.1.2. Bottom-up Segmentation

The bottom-up segmentation approach merges smaller objects into larger ones. The algorithm can, but must not start with a pixel of an image as a basis. The multiresolution segmentation and the classification based segmentation are examples of this approach. (DEFINIENS AG 2007a)

The

Figure 3 shows a bottom-up approach that starts with the pixel level. The resulting image objects are built up of pixels and form the entire image.

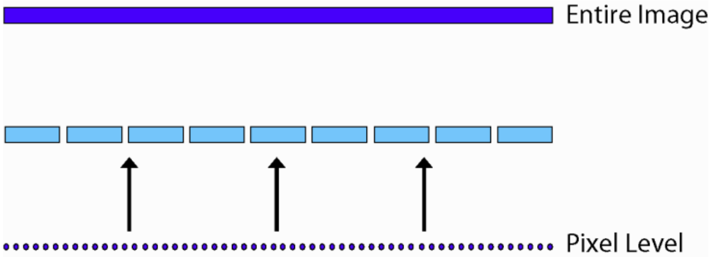


Figure 3: Bottom-up segmentation approach. Source: DEFINIENS AG 2007a.

Bottom-up methods differ between three types of image objects: the seed, the candidate and the target. Their coherence is obvious in Figure 4 pixels are merged according to a specific logic. An active image object is called a seed. Candidates are pixels which come into consideration as possible merging objects. The target is the resulting image object, if the pixels and the potential candidates are merged. The figure below shows the correlations between these three terms. (DEFINIENS AG 2007a)

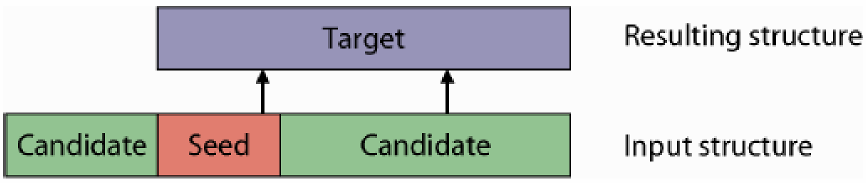


Figure 4: Image object types. Source: DEFINIENS AG 2007a.

- Multiresolution segmentation

The multiresolution segmentation considers each pixel as an object and merges them into larger image objects, also referred to as a segment. The algorithm can be based on the pixel level or on an already existing image object level. The basis is the similarity and homogeneity between nearby pixel objects. This algorithm is based on a region growing approach. The user defined scale parameter determines the maximum allowed heterogeneity. This parameter also defines the size of the segments created within this algorithm. The scale parameter needs to be smaller for heterogeneous image data than for homogenous. The smaller the size of the parameter, the larger the number of the resulting segments in an image will be. Thus, a high scale parameter leads to fewer segments. The user can define several values within the segmentation process and therefore decide how many iterations are executed. The multiresolution segmentation offers the possibility to apply segmentations at different levels. This has the advantage that certain classes can have a smoother segmentation than other ones. The user also has the option to weight the image layers of the image differently. Furthermore, the homogeneity criterion that is built up of spectral and shape criteria must be defined. The figure below on the right side shows an image, and on the left is the result of an applied multiresolution segmentation. Unlike the approaches mentioned before, there are no squares and grids. (DEFINIENS AG 2007b)

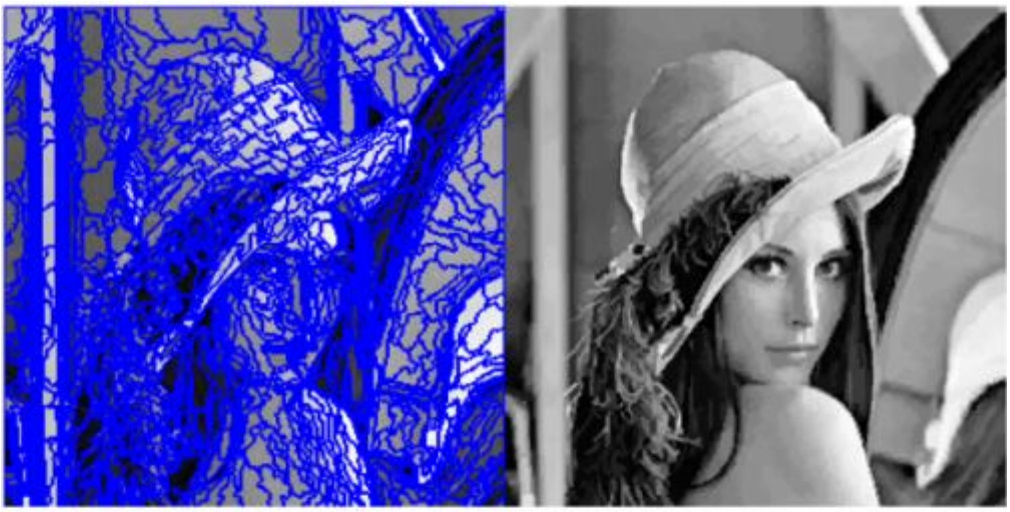


Figure 5: Result of a multiresolution segmentation. Source: DEFINIENS AG 2007b.

To express this concept simply, the multiresolution segmentation can be explained in the following way:

1. The algorithm starts with an image object with the size of one pixel. These pixels are merged into larger objects during several successively iterations. The iterations stop when the homogeneity criterion is reached. The criterion is a combination of spectral and shape homogeneity values. The user can influence this process by taking into consideration the definition of the scale parameter, as formerly mentioned, the number of resulting segments depends on the size of the scale parameter.
2. Figure 6 shows that the actual seed pixel, searches among its neighbors for the best merging mutual candidate.
3. If a candidate is found like it is in the second image of Figure 6 , the algorithm checks if the seed pixel is also the best fitting candidate for itself. When the seed pixel is not mutual to the candidate pixel, the candidate pixel becomes the new seed pixel and the search for the best fitting neighbor starts again.
4. The pixels are merged if both pixels are the best fitting neighbors for one another like it is shown in the third image of Figure 6.
5. In every cycle of the algorithm every object is taken into account.
6. The algorithm stops when no objects can be merged during a cycle. (DEFINIENS AG 2007a)

Figure 6 shows an example of the above explained cycle of the searching for the best fitting mutual neighbor.

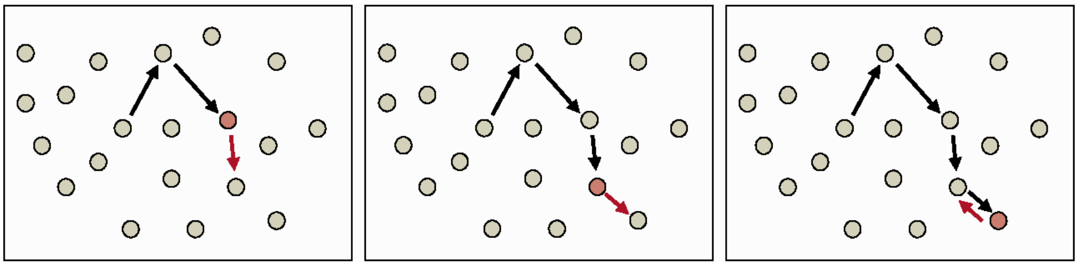


Figure 6: The process of the multiresolution segmentation. Source: DEFINIENS AG 2007a.

- Homogeneity criteria

The size of the scale parameter influences the homogeneity criteria, which depends on the parameters color, smoothness and compactness. The color is the primary parameter and creates significant segments while smoothness and compactness refer to the shape of an object. The shape criteria affect the quality of the objects. For example radar data can lead to fractured segments and the shape criteria can help to avoid those objects. (DEFINIENS AG 2007b)

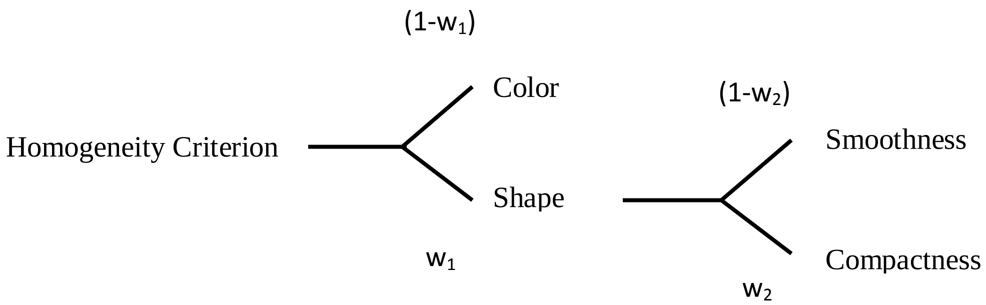


Figure 7: Composition of the homogeneity criterion. Source: own research vgl. "Definiens Developer".

Figure 7 displays the relation between the parameters of the homogeneity criterion. The shape parameter (w_1) can have a value between 0.1 and 0.9. The weight of the color criterion depends on the shape criterion, according to the formula $1\text{-}w_1$. The compactness criterion (w_2) can also have a value between 0.1 and 0.9. The compactness influences the weight of the smoothness parameter. The formula for the dependence between compactness and smoothness is $1\text{-}w_2$. (DEFINIENS AG 2007a)

  - Color and shape

The shape parameter determines the influence the spectral values of the image have on the homogeneity criterion. The homogeneity criterion is weighted with a value of 1. If the shape criterion has the weight of 1, the color criterion has no influence on the segmentation, because no spectral data is considered. Therefore, the highest value the shape criteria can be is 0.9, due to fact that the spectral information of image objects is necessary for the classification. The shape criterion is composed of the parameters smoothness and compactness. (DEFINIENS AG 2007b)

- Smoothness and compactness

The smoothness criterion deals with the borders of image objects. Its purpose is to modify the borders of the segments. The smoothness is especially important in regard to heterogeneous data, because the borders of image objects could fray. Avoiding image objects with frayed borders is important. The compactness criterion on the contrary is responsible for the compactness of an image object. This criterion should be applied if compact segments exist within an image but are separated from less compact segments only via weak spectral contrast. (DEFINIENS AG 2007b)

5.2.2. Classification

A classification of image objects requires the definition of classes based on thresholds, class descriptions, algorithms, etc... The class definition depends on the applied classification algorithm. These classes can be defined inside the class hierarchy window. The image objects are assigned to a class with the best fitting criteria. The different ways to classify the image objects are explained in the following passages. (DEFINIENS AG 2007a)

5.2.2.1. Algorithms for process-based classification

This method distinguishes four different classification algorithms. The assign class approach for example that uses certain features to assign an image object to a class. This approach is the most simple and uses thresholds to assign a segment to a class. Next the classification approach employs the descriptions of classes to assign an image object to a certain class. The third option is the hierarchical classification approach that is based on the class description and the hierarchical structure of the classes. At last there is the advanced classification algorithm, which is used to execute a specific classification. An example of this is the localization of extremes or the identification of relationships between classes. (DEFINIENS AG 2007a)

5.2.2.2. About Classification with Class Descriptors

Thresholds, membership functions, similarities and nearest neighbor samples can serve as class descriptors. It is possible combine these descriptors for a classification. Logical operators can be combined as well. Thresholds are used when a feature can differ between classes. The membership functions allow the user to define border values. A relationship between values and the level of the class membership is given. (DEFINIENS AG 2007a)

5.2.2.3. Nearest neighbor

This classification algorithm consists of two steps. Primarily the user collects samples for each class. The image objects are then classified according to these samples. (DEFINIENS AG 2007a)

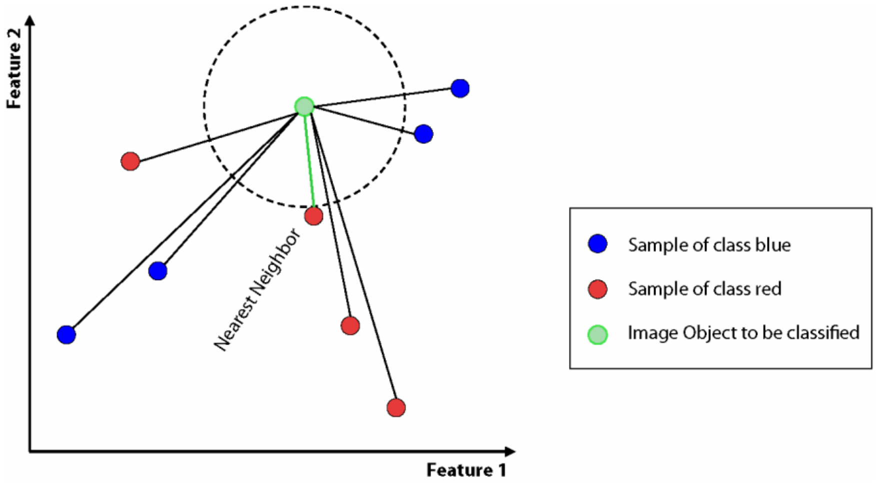


Figure 8: Nearest neighbor classification

Figure 8 shows how the nearest neighbor classification algorithm works. The algorithm searches the neighbors of an image object according to the best fitting neighbor.

"The Nearest Neighbor classifier returns a membership value between 0 and 1 based on the image object's feature space distance to its nearest neighbor. The membership value is 1 if the image object is identical to a sample. If the image object differs from the sample, the feature space distance has a fuzzy dependency on the feature space distance to the nearest sample of

a class. You can select the features to be considered for the feature space." (DEFINIENS AG 2007a)

In the practical work of this master's thesis the assign class algorithm is used, because the classification is based on thresholds and neighborhood relationships. The classification procedure was done inside the "Process Tree" window. Here the user can define rules for the classification of the segments. The object features and the class related features which are explained in chapter 5.2.3.1 and 5.2.3.2 are essential to these rules. (DEFINIENS AG 2007b)

5.2.3. Classification features

5.2.3.1. Object features

Object features result from the evaluation of image objects and their position in the image object hierarchy. The object features can be distinguished in seven different ways:

Customized

Customized features allow the user to create new features that are necessary for the classification. It is possible to calculate new features in the "Edit Customized Feature Window". The user can compute additional values like the NDVI, which can serve as a classification parameter. (DEFINIENS AG 2007a)

Layer values

The layer values show the spectral information in the green, red, near infrared, mid-infrared and the panchromatic image layer of the image objects. Then the mean value and standard deviation of an image object are calculated. Additionally the relationship to other image objects is considered. The layer values also offer information about the brightness and the max. difference of a pixel. The information of the max. difference results from the subtraction of the minimum mean value of an image object from its maximum mean value. To get these values the minimum and maximum values of all given layers are compared. The resulting value is than divided by the brightness value. (DEFINIENS AG 2007a)

Shape

The shape parameters provide information about the shape of an object with regard to the area, length, width et cetera. These characteristics are calculated based on the pixels that form an image object. Due to the hierarchical structure, other parameters based on the analysis of sub-object features can be computed. The shape parameters that were used for the practical work within “Definiens Developer” are briefly defined in the following passages. (DEFINIENS AG 2007a)

- Area: If the satellite data is not georeferenced, the area of a single pixel is 1. An image object consists of several pixels and therefore the extent of an object is the sum of these pixels. If the data is georeferenced, the area of a pixel is the area covered by a pixel. The image object area is again the sum of the area of all the pixels that form the image object. (DEFINIENS AG 2007b)

- Asymmetry: The longer an image object the higher the asymmetry of the object will be. This is the ratio of the length of the minor to the major axis, which the ellipse expresses; an ellipse is converged to the image object. Asymmetry can have a value between 0 and 1. The figure on the right side shows an ellipse, which encloses an image object at the minor axis n and the major axis m. (DEFINIENS AG 2007b)

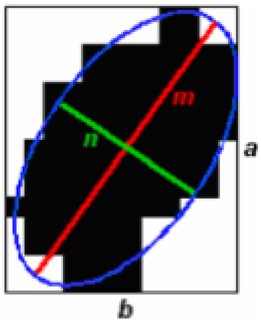


Figure 9: Ellipse that encloses the image object.
Source: Definiens AG 2007b

- Border Index: This feature searches for the smallest rectangular as an approximation to the image object. This rectangular should enclose the image object. The ratio between the border length of the segment and the border length of the rectangle is calculated. The range of the border index is between 1 and ∞, but the ideal value is 1. A fractal image object leads to a high border index. Figure 10 shows in red the length of the rectangular, the yellow object

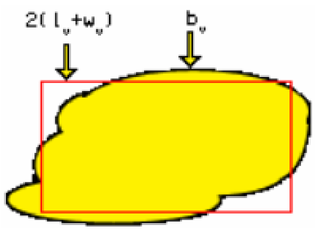


Figure 10: Approximation of the rectangular to the image object.
Source: Definiens AG 2007b

represents the image object. The formula expresses the ratio between the border length of the segment (b_v) and the border length of the rectangular ($2(l_v+w_v)$). (DEFINIENS AG 2007b)

- Border length: The sum of all the edges of an image object results in the border length of the segment. The edges can share a border with other image objects or are situated at the edge of an image. The length of the edge of the pixels in non geo-referenced image data is 1. The border length can have a value between 0 and ∞. Figure 11 shows an example for the border length of the object "v" and the shared border length between "v" and "u". (DEFINIENS AG 2007b)

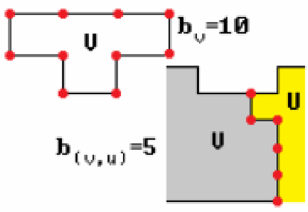


Figure 11: Examples for the border length of an object and a shared border. Source: Definiens AG 2007b

- Compactness: The compactness of an image object is based on the area. The compactness feature has an affinity to the border index, which is border based. The compactness is the product of the length l and the width "v" of an image object. This product is then divided by the number of pixels in the image object. The compactness can have a value between 0 and ∞, but the ideal value is 1. The smaller the border of an object, the more compact the image object will be. (DEFINIENS AG 2007b)

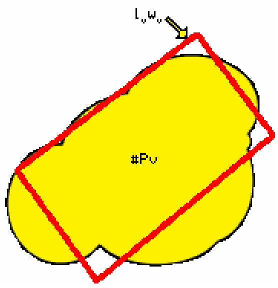


Figure 12: Compactness of an image object. Source: Definiens AG 2007b

- Length: To calculate the length of an image object, the ratio of the length to the width is used. This feature can have a value between 0 and ∞. The number of pixels forming the image object are also used. The following formula shows the calculation of the length feature. The value "P_v" represents the total number of pixels of the feature, "y_v" is the ratio of the length to the width. (DEFINIENS AG 2007b)

$$\sqrt{\#P_v \cdot \gamma_v}$$

Figure 13: Formula to calculate the length. Source: Definiens AG 2007b

- Length/Width: There are two possibilities to calculate the ratio of the length to the width of an image object.
  - *"The ratio length/width is identical to the ratio of the eigenvalue of the covariance matrix with the larger eigenvalue being the numerator of the traction:" (Definiens AG 2007b)*

  - *"The ratio length/width can also be approximated using the bounding box:" (Definiens AG 2007b)*

Both of these methods are used to calculate the ratio of the length and width in the "Definiens Developer" software. The length/width feature is expressed by the smallest calculated value of both methods. (Definiens AG 2007b)

- Rectangular fit: Similar to the elliptic fit a rectangle with the same size as the image object is created. This approach compares the area of the image object outside of the rectangle to the area inside of it. (Definiens AG 2007b)

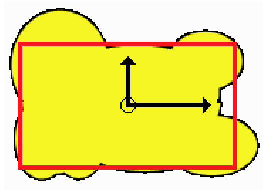


Figure 14: Comparison of area inside and outside of the rectangular Source: Definiens AG 2007b

- Width: To express the width of an image object, the ratio of the length to the width is computed. The feature width can reach a value between 0 and ∞. To calculate the value the number of pixels "P_V" which form the image object is required. Figure 15 shows the calculation of the feature. (Definiens AG 2007b)

$$\boxed{\frac{\#P_v}{\gamma_v}}$$

Figure 15: Formula to calculate the width. Source: Definiens AG 2007b

<u>Thematic Attributes</u>

Thematic layers include thematic attributes which are used to describe image objects. The attributes are listed within the "thematic attribute table". . Each thematic attribute has its own ID and each object is represented by another color. The most important feature of the thematic attributes is the "number of overlapping thematic objects". This parameter is important for the classification of the image objects. Image objects can be overlapped of the objects within the thematic layer. If this is the case, the image object has a value of lager than 0. (Definiens AG 2007b)

Texture

The texture of image objects depends on their sub-objects. Therefore it is mandatory that an image object level exists. There are three groups of texture features, those that deal with the spectral form, those that deal with the shape of the sub-objects and the features that refer to the gray level co-occurrence matrix (GLCM). The GLCM features calculate the different combination of gray level possibilities of an image. The GLCM offers four directions, 0°, 45°, 90° and 135°. The information of all four directions summed up calculates the directional invariance. The figure below shows that the vertical direction is represented by the 0° angle, while the 90° angle represents the horizontal direction. In the "Definiens Developer" software, the GLCM is calculated for every pixel included in an image object. Additionally the GLCM is also calculated for the pixels situated on the direct border of an image object. This is done to reduce border errors. Elements that are situated in the diagonal of the matrix represent pixels with no gray level difference. The greater the distance from the diagonal, the greater the gray level difference will be. The texture according Haralick offers several features that can be calculated for all directions of, 0°, 45°, 90° and 135°. (DEFINIENS AG 2007b)

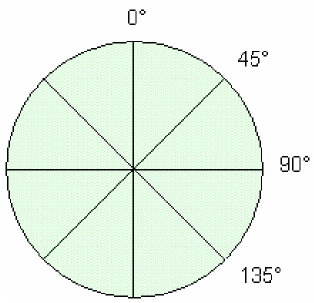


Figure 16: GLCM. Source: Definiens AG 2007b

The other object features like the variables and hierarchy are not relevant for the practical work of the master's thesis. Therefore they are only briefly discussed in the following passage.

The texture features are used to distinguish the image objects according to their texture. The software "Definiens Developer" offers the user several different texture parameters. The variables describe values related to the other variables. The hierarchy characteristics display information about the image object level of a segment. This information is important in regard to the class hierarchy, if the classification is based on multiple different image object layers. (DEFINIENS AG 2007a)

5.2.3.2. Class related features

The class related features depend on the characteristics of the image objects. The classes, their neighborhood and the class hierarchy are of great importance for these features. The features include relations to neighboring objects, sub-objects, super-objects, classification and customized features. (DEFINIENS AG 2007a)

<u>Relations to neighbor objects</u>

The mutual relationship of one image object to its neighbors is of major importance to describe an image, and assign it to a specific class. This feature assumes that the image objects are within the same image object level. The "Definiens Developer" offers several different features to calculate relations to neighboring objects. These features are shortly declared within this chapter. (DEFINIENS AG 2007a)

- Existence of: The existence of image objects of a specific class within a certain perimeter around a selected image object is considered. The feature's distance defines the perimeter. If the feature has the value 1, the image object of a certain class is within the perimeter, a value of 0 represents the opposite. (DEFINIENS AG 2007b)

- Number of: This feature counts the number of image objects belonging to an actual class within the perimeter around an image object. The "number of" feature can reach a value between 0 and ∞. (DEFINIENS AG 2007b)

- Border to: The border to feature concerns the absolute border that an image object shares with its neighbors of a defined classification. If georeferenced data is used, the value represents the real border to the image objects of a specific class. If non georeferenced data is given, the "border to" value is calculated by pixels edges, which a concerned image object shares with its neighbor. The length of the edge of a pixel is 1. Therefore the "border to" feature can reach a value between 0 and ∞. The figure shows the absolute border between classified and other unclassified segments. (DEFINIENS AG 2007b)

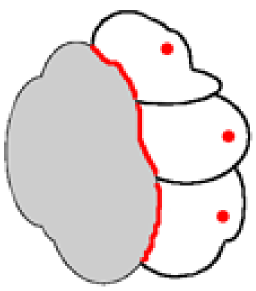


Figure 17: The red line represents the border between the selected image objcet and ist neigbhors. Source: Definiens AG 2007b

- Relative border to: This feature concerns the relative length of the border that an image object shares with its neighbors. The "relative border to" value results from the ratio between the length of the border an image object shares with its neighbors of a certain class and the total length of the image object border. This feature can reach a value between 0 and 1. The value 1 declares that an image object is completely surrounded by another image object. The relative length of an image objects is denoted in pixels. The figure shows an image object that is surrounded of other objects. B_v expresses the length of the border of the image object. (DEFINIENS AG 2007b)

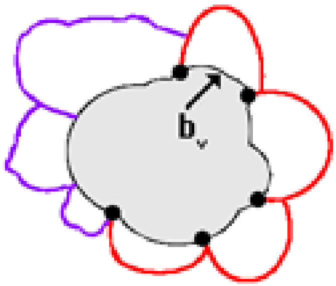


Figure 18: Relative border between the classified segment and its neighbors.
Source: Definiens AG 2007b

- Relative area of: To express this feature, the area of a selected class in a user defined area is divided by the total defined area. The "relative area of" feature can reach a value between 0 and 1. If the value of the feature is 1, the image object is totally enclosed by a class. Whereas the value 0 states that a class does not exist. (DEFINIENS AG 2007b)

- Distance to: The "distance to" feature is expressed in pixels. The feature concerns the distance from the center of an image object to the nearest center of a segment of a certain class. All objects that are on this line need to be of this certain class. The distance to feature can reach a value between 0 and ∞. The figure to the right shows the distance between the centers of the selected image object and the nearest neighbor of a selected class. (DEFINIENS AG 2007b)

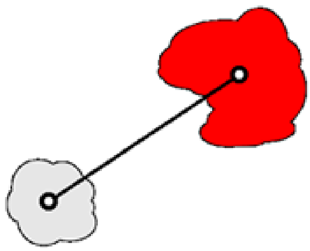


Figure 19: Distance between the centers of two image objects. Source: Definiens AG 2007b

Relations to sub-objects

According to the relations to sub-object features, the relationships of image objects to other image objects of a given class inside a lower image object level are considered. The lower the image object level, the higher the resolution of the image objects will be. (DEFINIENS AG 2007a)

Relations to super-objects

This feature concerns the relationship of image objects to other image objects of a given class within a higher image object level. As the resolution of an image object decreases the higher the image object level becomes. (DEFINIENS AG 2007a)

Relations to classification

This feature gives the user information about the actual classification of a segment. Through which the name of the class of an image object can be expressed. The user can enter the value 0 in the "Distance in Class Hierarchy" window. This states that there is only one hierarchical level and therefore the name of the class is expressed. (DEFINIENS AG 2007a)

5.2.3.3. Thematic Layer

During a "Definiens Developer" project it is possible to add thematic layers. They offer additional information of the project. These layers can have a raster or vector format. However, they are allowed to contain only one type of object. These objects can be a line, point or polygon. Image layer and thematic layer are treated differently during the segmentation process. A thematic layer can also be added in an already existing project. Shape files can be very easily added as a thematic layer, although it is important that it only includes polygons, because other types of object are not supported. A vector file needs to be converted into a raster file before it is imported to the "Definiens Developer". (DEFINIENS AG 2007a)

To illustrate a thematic layer in a "Definiens Developer" project, the user must select the main menu and choose "View" and then "View Settings". The Figure 20 shows the settings of the image layers within the "View Settings" window. The user must right-click on the layer and then all thematic layers within the project are shown. The user can now distinguish between these layers. (DEFINIENS AG 2007a)

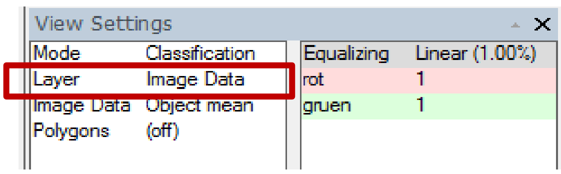


Figure 20: View settings window in Definiens Developer. Source: own research in "Definiens Developer".

The chosen layer is now illustrated in the main window of the “Definiens Developer”. All objects that are contained in the thematic layer are displayed in a different color. Figure 21 shows an extract of the thematic layer “wetland”. Every occurring image object is clearly displayed in another color. (DEFINIENS AG 2007a)

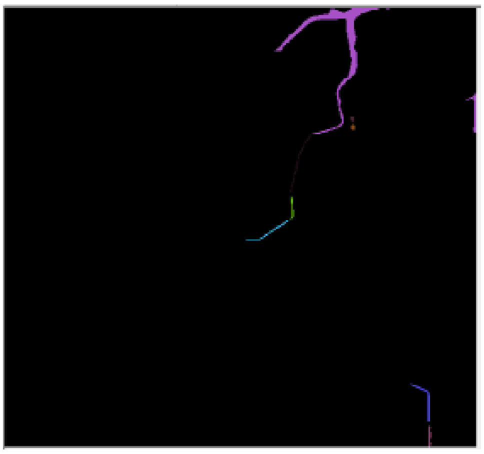


Figure 21: Extract of the thematic layer “wetland”. Source: own research in “Definiens Developer”.

The thematic layers can also be used in a segmentation process. Thereby the thematic layers need to be active layers. These layers influence the creation of segments within an image. If the segmentation process is based on the thematic layers, the weighting of the image layers need to be adjusted to 0. When the segmentation is based on thematic layers, only the processes multiresolution segmentation, spectral difference segmentation or multiresolution segmentation region grow can be applied. (DEFINIENS AG 2007a)

5.2.3.4. Use customized features

In the customized features option, the user can create new features. There are two different types of customized features, the arithmetic and the relational features. Arithmetic features contain already existing features, variables or constants that can be combined with arithmetic operations. Arithmetic characteristics are composed of multiple features, but they describe only one image object. In the practical approach of the master’s thesis the NDVI was calculated as an additional attribute. The red and the near red bands are necessary for this calculation. (DEFINIENS AG 2007b) Relational features compare the attribute of one object to other related objects of a certain class within a defined distance. Relational features can be surrounding objects, sub-objects, super-objects or an image object level. Contrary to the arithmetic features these features consist of only one attribute, but they describe a group of image objects. (DEFINIENS AG 2007b)

5.2.4. Methods for accuracy assessment and error matrix

The quality of a classification result is determined with the help of an accuracy assessment. Within the work of the master's thesis the accuracy of the classification result is calculated with the help of an error matrix. The following Table 4 explains the performance of an error matrix according to an example.

Table 4: Example for an error matrix

Reference data								
Source data		Settlement	Forest land	Grassland	Cropland	Total		User accuracy
	Settlement	20	0	0	3	*23*		86,96%
	Forest land	0	10	7	0	*17*		58,82 %
	Grassland	0	5	15	2	*22*		68,18 %
	Cropland	0	2	1	5	*8*		62,5 %
	Total	*20*	*17*	*23*	*10*	*70*		
	Producer accuracy	100 %	58,82 %	65,22 %	50 %			71,43%

First, the number of random points of the class settlement in the source and in the reference data is recorded. The other columns include the number of random points that are of the class settlement in the source data, but forestland, grassland or cropland in the reference data. The same procedure is done for all other classes. Then, the sum of each column and row is calculated. In the example altogether there are 70 points. Additionally all points that have the same class in the source and reference data are calculated, represented by 50 (20+10+15+5) in the example.

Next, the accuracies are calculated. The overall accuracy is expressed by the sum of all random points that have the same classification in the source and the reference data, divided by the number of the calculated random points. Additionally the producer's and user's accuracy is calculated. The producer's accuracy defines how well an area is classified, whereas the user's accuracy compares the classified images in the map with appropriate class on the ground.

6. Workflow and parameters in “Definiens Developer” and “ArcMap”

This chapter deals with the process of a classification itself. Primarily the theoretical workflow of a classification is discussed. Then the workflow of the classification of Singapore within the master’s thesis will be explained.

6.1. Theoretical workflow

6.1.1. Establishing a new project

The first step in this process involves applying a new project in the “Definiens Developer” software. An image is loaded into the project. The spectral layers can be renamed for a better understanding, the layer one for instance corresponds to the green band within the “Spot 5”. Given thematic layers they can also be added. The figure below shows the “Create Project” window, where the major adjustments can be done. A name for the project can then be assigned. Next, basic information of the image is listed. After which, the image layers are given, followed by the thematic layers. Additionally, it is possible to include metadata, like a cadaster.

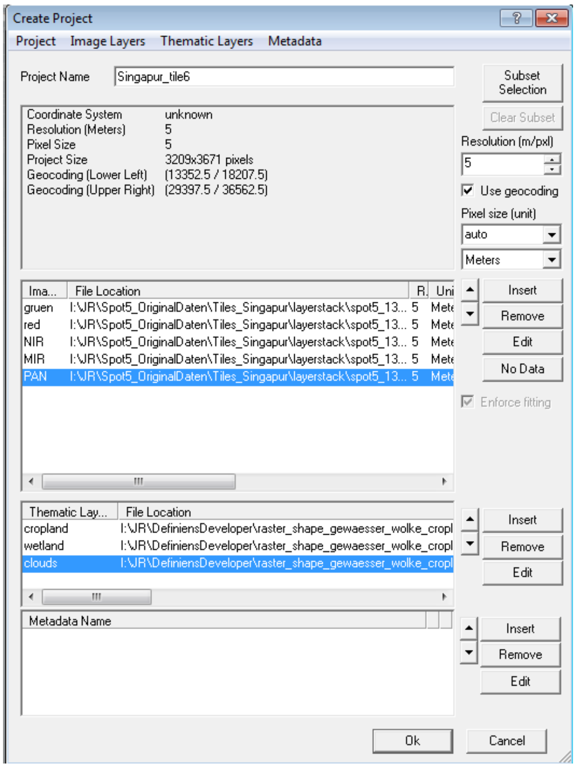


Figure 22: Create Project window. Source: own research in “Definiens Developer”.

In the main window of the “Definiens Developer” window the field “develop rule sets” can be activated. This opens the “process tree”, the “class hierarchy”, the “image object view” and the “feature view window”. In the” process tree” window all settings with regard to segmentation and classification are listed. The “class hierarchy” window enables the user to define the classes for classification. The “image object” window includes information such as spectral values, area and shape of a selected segment. The “feature view” lists the features available to the user. They are ordered as such: object features, class related features, scene features, process related features and customized features. The figure below shows an example of these windows and the displayed information’s.

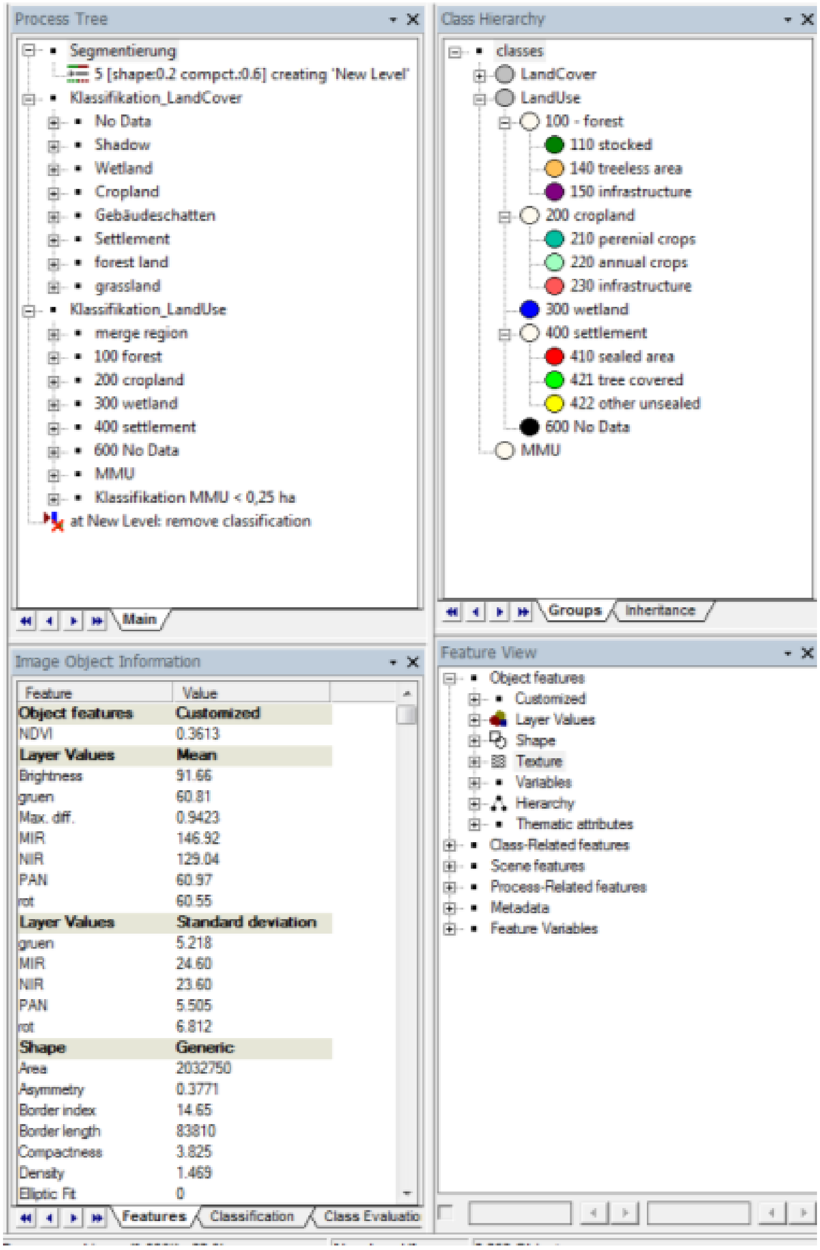


Figure 23: The develop rule set windows. Source: own research in “Definiens Developer”.

6.1.2. Segmentation

The process tree window must be activated for the segmentation process in the “Definiens Developer” software. To do this, the user opens the “edit process” window by right-clicking the “process tree” window. In this window the most important features for the segmentation process are defined. The definition of the segmentation algorithm is of critical importance. The user must define the image object domain, because this is the level at which segmentation is executed. Then the name of the actual level must be assigned. The layers of the image can be weighted differently and possibly given thematic layers can be activated in the segmentation settings. The influence of the scale parameter and the homogeneity criterion were explained in the subchapter “multiresolution segmentation” of the chapter 5. The classification is applied on the basis of the result of the segmentation.

The figure below shows where the user must adjust the major important parameters for the segmentation process.

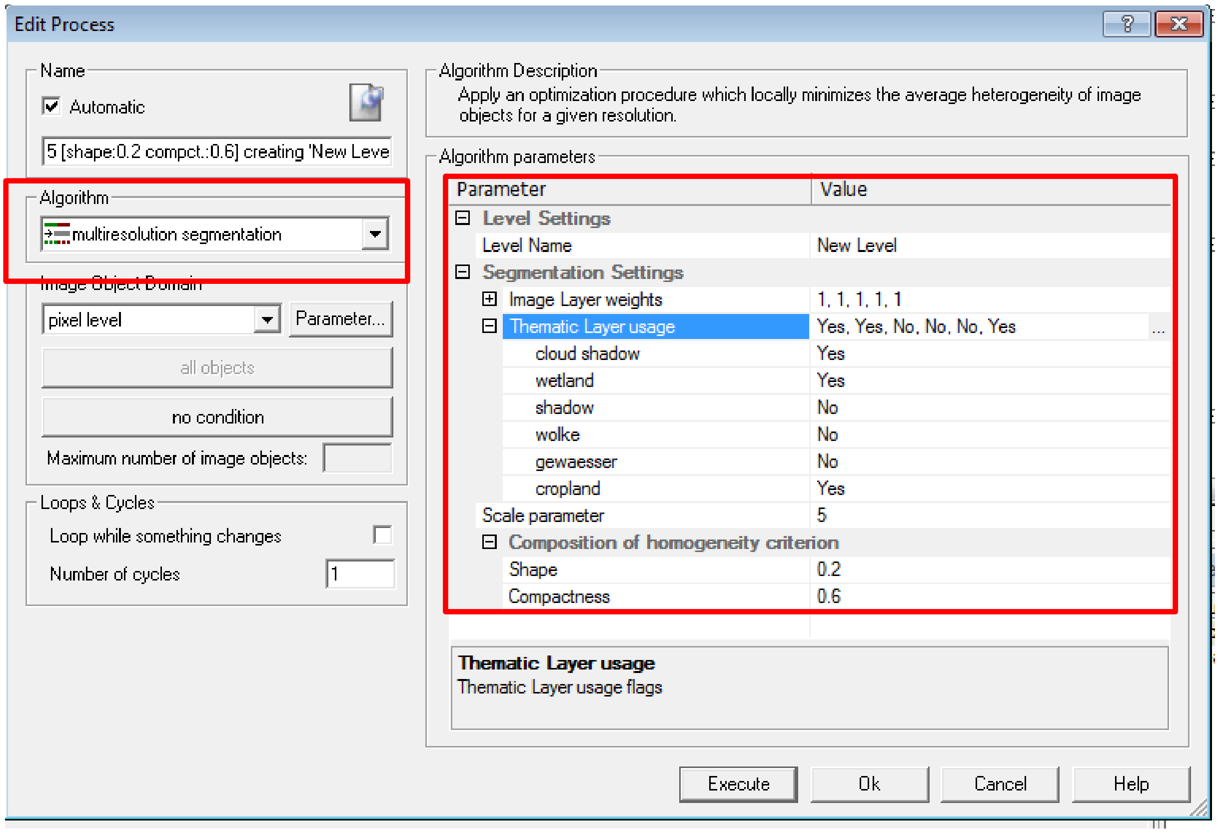


Figure 24: Settings for the segmentation process. Source: own research in “Definiens Developer”.

6.1.3. Export data

The “Definiens Developer” offers several methods to export the results of the classified data. The classification can be exported as graphic data in a vector or raster format. The statistical information of the data can also be exported. The software offers three different options to export the data: First, the export can be performed using a command within the rule set. Before this is done, how and where the data will be exported must be defined. The second export option defines an action for how and where the data will be exported. The third possibility is to export the results via the export menu. To do this action, the user can choose which classes and related information have to be exported. In addition the user needs to define the name, type and storage location of the export. The classification can also be exported as a vector or raster file. Therefore an additional .csv file which includes attribute values of the classification can be exported. Shape files on the contrary can be exported together with their attribute values. (DEFINIENS AG 2007a)

The classification results of the this work were exported using third method, because certain information like the area, length, width and class name were addtionally exported for each calculated image object. Figure 25 shows the “Export Results” window and the applied adjustments. The classification result was exported as a shapefile with polygons as content type. The window “Classes” includes all classes that were exported and the “Features” window shows the exported information of the polygons.

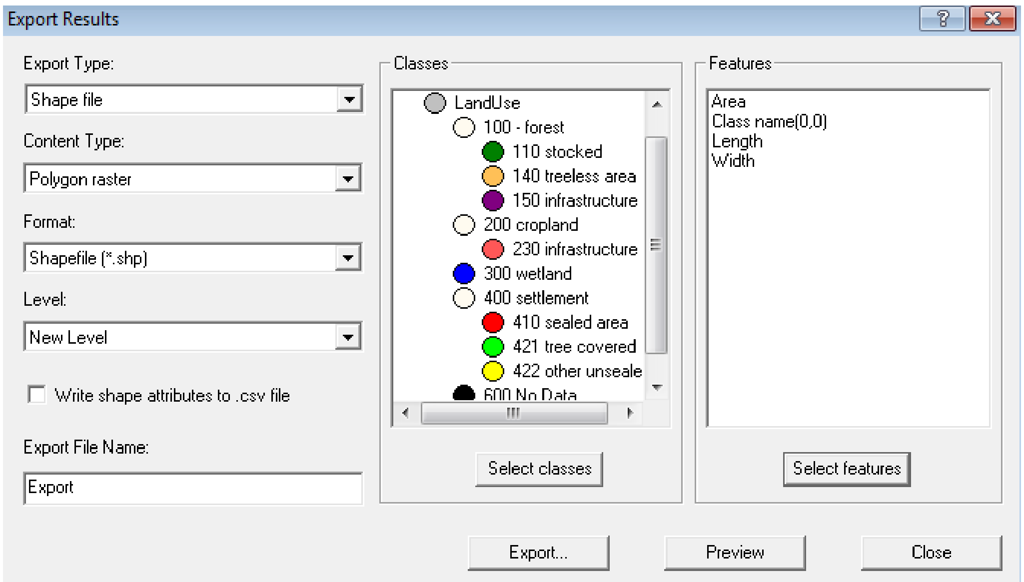


Figure 25: Export Results window. Source: own research in “Definiens Developer”.

6.1.4. Accuracy Assessment

It is important to execute an accuracy assessment process on a classification result in order to give the user information about the quality of the result. During this process the classified data is compared with satellite image data or aerial photographs. (VIRGINATECH 2009)

- Definiens Developer

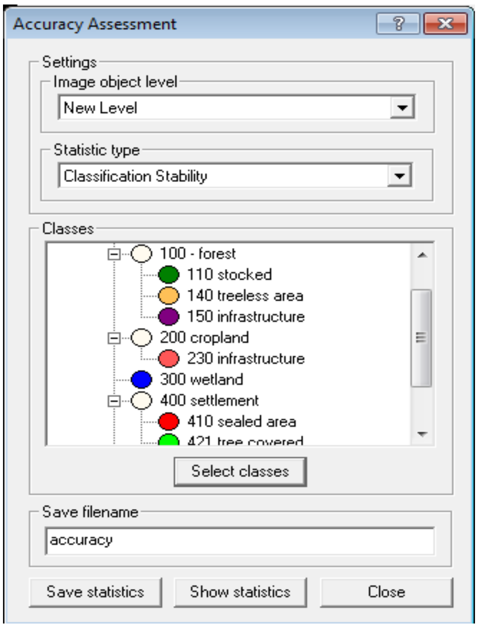


Figure 26: Accuracy assessment window. Source: own research in "Definiens Developer".

Accuracy assessment methods are used to create statistical data outputs. These statistical data outputs are exported in a .txt file, whereas graphic data is exported in a raster format. The "Classes" window shows all classes of an image and their hierarchical adjustment. The "Show Statistics" button reveals the results of the accuracy assessment. The results can be exported, bur first need to be safed. The user needs to define multiple parameters inside the accuracy assessment window. First, the proper image object layer needs to be defined. (DEFINIENS AG 2007a) The drop down list of the statistic type offers four different accuracy assessment approaches:

  - Classification stability: If this method is selected, a new window opens. Within this window the calculated statistical values are displayed. The calculated values are expressed in percentage values, and are calculated by the difference between the best and the second best class assignment. The statistical values are the number of the image objects within a class, the mean, the standard deviation, and the minimum and maximum value of a class. (DEFINIENS AG 2007a)

- Best classification result: The statistical results that are computed within this accuracy assessment approach are displayed in a dialog box. The values for the best classification of a class are shown within this box. The number of image objects for a class is calculated as well as the mean, the standard deviation, and the minimum and maximum value. (DEFINIENS AG 2007a)
- Error matrix based on TTA (training and testing area) mask: This approach also displays a bounding box that includes the statistical values of the accuracy assessment. The quality of the classification result is checked with the help of test areas. The pixel based test areas are compared to the result of the classification. (DEFINIENS AG 2007a)
- Error matrix based on samples: This method shows affinities to the former accuracy assessment method, but manually located samples are considered instead of the pixels. The classification result is compared to these samples. If a match it is found, it is expressed in class samples. (DEFINIENS AG 2007a)

- ArcMap

The user needs to create random points based on the actual classification result. In the "ArcToolbox" and the sub-item "Data Management Tools" the user selects "Feature Class" and "Create Random Points". Then, a new window appears and the user can define the output location, the name of the output file, and the extent number of the calculated random points. The new computed file is loaded into "ArcMap". Next the user has two possibilities, either uses the high resolution satellite imagery within "ArcMap" for the comparison of the computed random points, or converts the point file into a "KML" file and compare it with "Google Earth" data. To export the random point file into a "KML" file the user must open the "Conversion Toolbox" and select "into KML". A new window appears and it is necessary to assign a name and the output location for the new file. "Google Earth" must be opened for this process. Now, the user can insert the "KML" file via the "File" and "Open" options in the main menu. After loading the random points, "Google Earth" zooms automatically to the investigation area. (VIRGINATECH 2009)

In "ArcMap" the user can add a new column in the attribute table of the random points file. This column contains the reference to the original classification. The attribute table contains the ID, the actual class number of the random points according to the land use classification result, and the reference column shows the class number that the random points have in

"Google Earth". All random points have to be regarded in "Google Earth". The user must record the class of the random point in the "Google Earth" data in the "ArcMap" attribute table in the reference column. The accuracy assessment based on the basemap within the "ArcMap" works the same way. When all random points are checked, the accuracy assessment is calculated. Then, the results of each random point are compared. The accuracy is calculated with the help of an error matrix. The structure of an error matrix is explained in chapter 5.2.4.

6.2. Practical workflow

6.2.1. Preliminary work for the classification process

The basis for the classification steps of the "Definiens Developer" are the four subsets of the "Spot 5" satellite image. The software is not able to edit the whole satellite scene, because of the size of the data. The satellite image was therefore split up in several smaller images the so called extracts and four of them were chosen for further adaption. The images were selected according to the given IPCC classes. The images should include as much classes as possible, because the resulting rule set should be the basis for the classification of the whole satellite image. It is an attempt to find out how the different circumstances in the single images influence the parameters within the ruleset. The sample images were used to adjust the selected parameters and therefore improve the accuracy of the classification. It turned out, that each single image required different parameters and values within the ruleset. The classification rule sets are based on thresholds concerning the five spectral layers, the shape, the texture, and neighborhood relationships. The threshold classification was applied because of the transparency of the classification. It is possible to classify each class individually for instance with regard to their spectral or shape characteristics.

6.2.2. Establishing the project

Primarily, a new project had to be established for each extract. For these projects it was necessary to define the given thematic layers for the class's wetland, clouds, and cropland. These layers are presented as shapefiles and were created during a preprocessing step. The thematic layers were digitalized with "ArcMap" based on the Spot 5 satellite data.

Figure 27 shows the adjustments of one of the projects. The user can assign a name to each project. In order to convey a better understanding, the name of the image layers can be changed. Assigning the spectral names of the layers is easier, for example: the layer 1 corresponds to the green band, layer 2 to the red, layer 3 to the NIR, layer 4 to the MIR, and layer 5 to the panchromatic. Then it is possible to add the three thematic layers in the project. After these adjustments have been made, the project can be created.

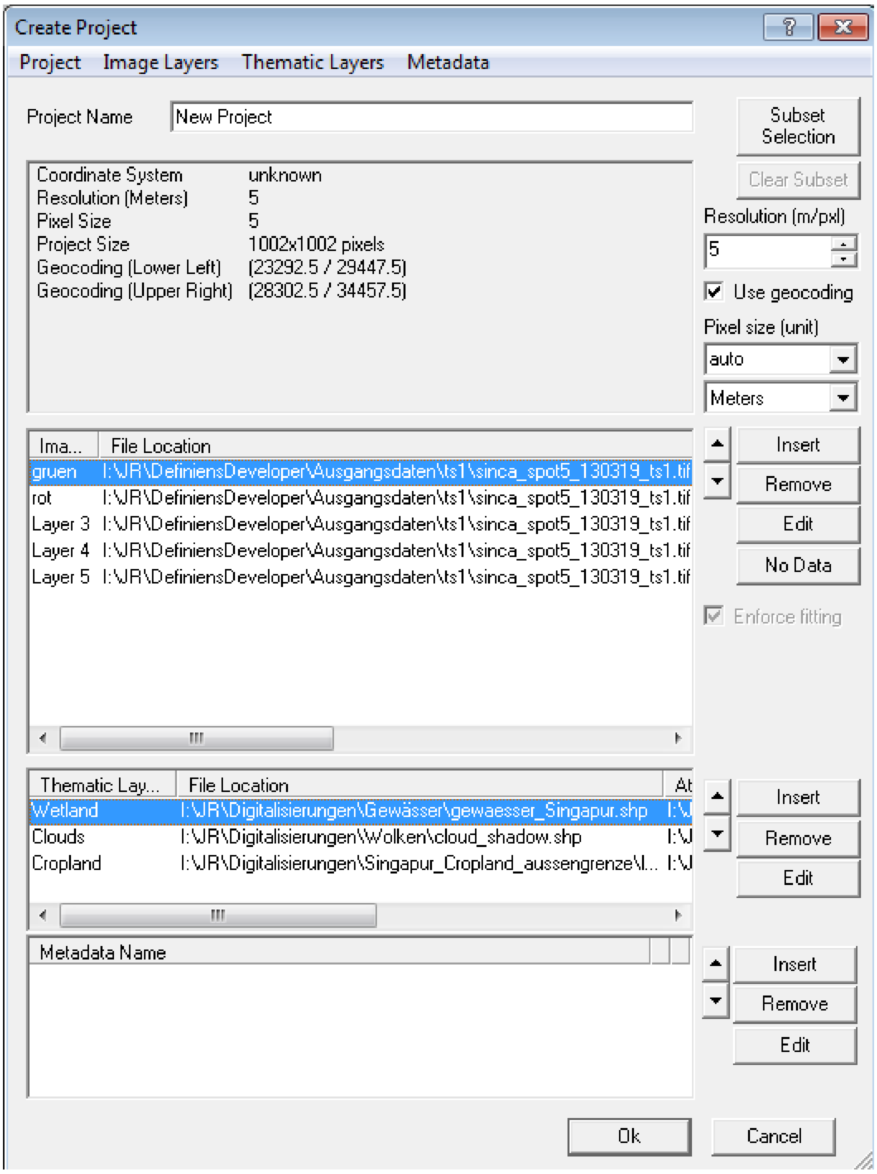


Figure 27: "Create Process" window. Source: own research in "Definiens Developer".

Implementation of the thematic layers and calculation of the NDVI were the first working step after a new project was generated, followed by the definition of the class hierarchy. The normalized difference vegetation index (NDVI) is a very powerful feature to distinguish between the image objects that belong to a vegetation class and other classes. Therefore, the window "edit customized features" was opened and the following formula was inserted:

$$(([\textbf{Mean NIR}] - [\textbf{Mean rot}])/([\textbf{Mean NIR}] + [\textbf{Mean rot}]))$$ [1]

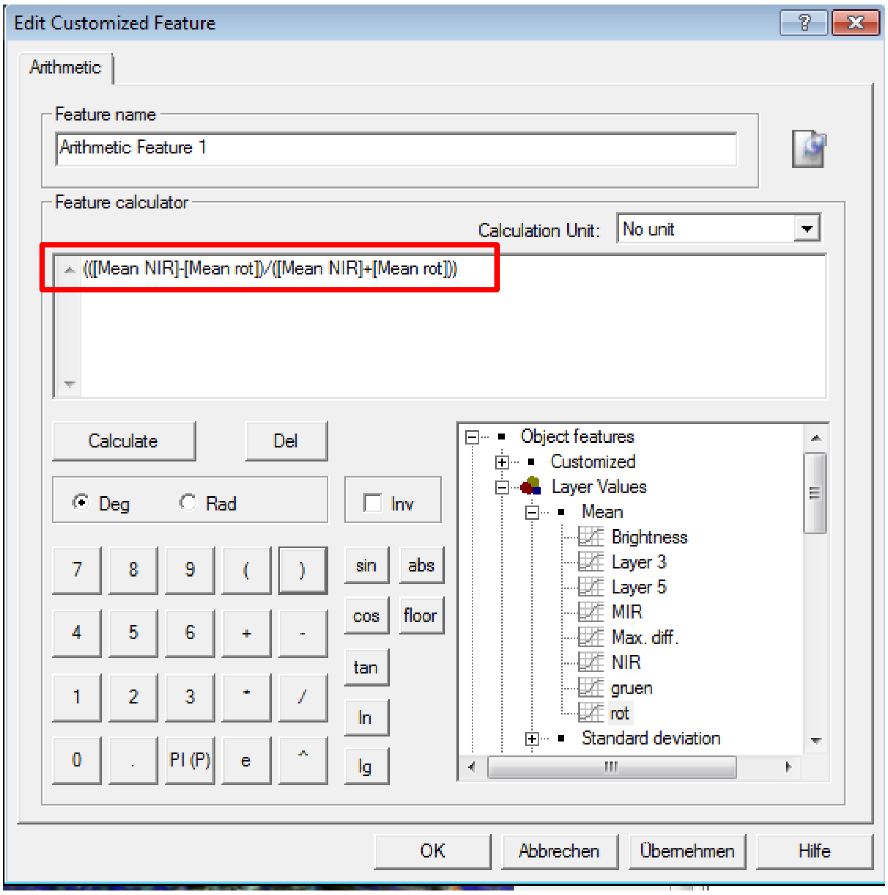


Figure 28: Calculation of the NDVI. Source: own research in “Definiens Developer”.

The definition of the land cover classes was the next step within the workflow. There are five main land cover classes, “forest land”, “cropland”, “grassland”, “wetland”, “settlement” and “no data”.

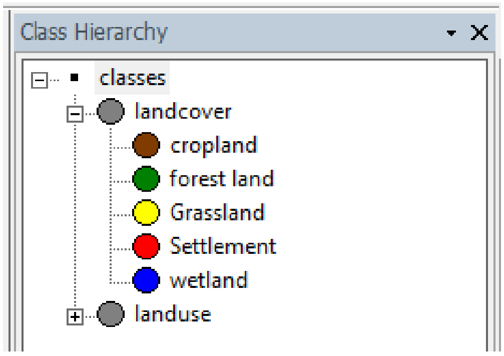


Figure 29: Land Cover class hierarchy. Source: own research in “Definiens Developer”.

6.2.3. Segmentation process

Figure 30 shows an example of the adjustments for the segmentation parameters. The single extracts and the combined image were segmented according to these adjustments. Thus, a comparison between the results of the two classification approaches was possible. The multiresolution segmentation was applied to the data. The basis of this bottom-up merge region process was the “pixel level”. Nearby pixels were merged into larger image objects according to similarities concerning their spectral and shape characteristics. Furthermore, a level name was assigned. All available image layers were equally weighted and the three thematic layers were active. The major important adjustments concerned the “scale parameter” and the “composition of homogeneity criterion”. The “scale parameter” was set to five, which meant that the resulting segments were significantly small and that the process compared the homogeneity criterion of nearby pixels and merges them into segments. After five iterations the process was stopped. After some attempts the shape parameter was set to 0.2 and the compactness to 0.5. This composition created adequate segments for the image.

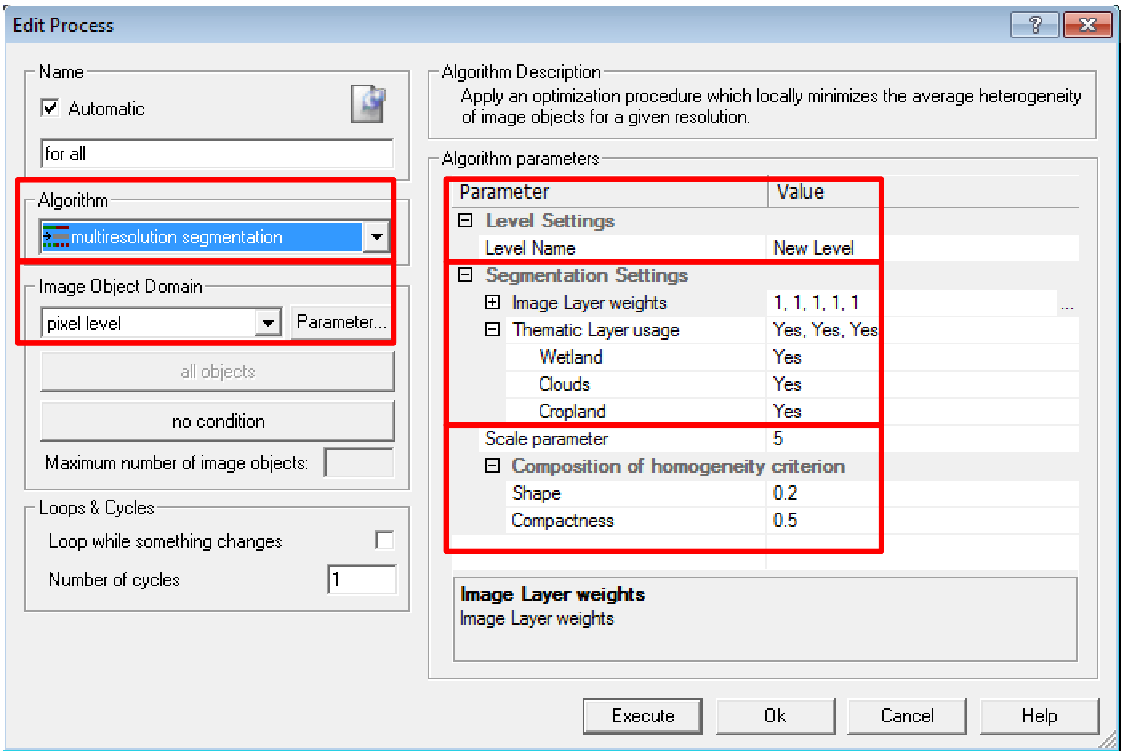


Figure 30: Segmentation adjustments. Source: own research in “Definiens Developer”.

6.2.4. Classification process

This chapter discusses the classification workflows for the four single images and the combined image. These samples images represented the adapted IPCC classes very well. Due to the fact that each single image required a distinct ruleset, they were combined to a new image. The classification of the combined rule set was the basis for the classification of entire Singapore. Primarily, the images were classified with regard to the land cover. The land use was derived from the resulting land cover classification. Thematic layers are given as additional information for the classification. The meaning of the thematic layers was annotated in chapter 5.2.3.3. A layer for the class's wetland, cropland and cloud shadow is given. This additional information is necessary, because of spectral similarities. It is very difficult to classify these classes with the help of a rule set only. These class layers were therefore generated with the "ArcMap" software. An own layer with already existing image objects was applied for this classes. Unclassified image objects that were overlapped by a thematic layer were assigned to the land cover classes "wetland", "cropland" and "cloud shadow". An accuracy assessment is performed to estimate the quality of the classification result. The workflow of the accuracy assessment is described in chapter 7.

6.2.4.1. Classification approach of the single extracts

Although the four sample images were extracted from the same Spot 5 satellite image, they differ from each other due to atmospheric influences, different tree species and similarities between land use classes. Therefore, they require a different set up of classification parameters. In the following passages, the classification rule sets for each sample images are discussed. The process tree for each classification is displayed for a better understanding. The applied rules and the corresponding thresholds and values are obvious.

- Image 1

In the beginning, the image objects were assigned to a specific class with regard to the thematic layers. The next step was to classify those segments that represent shadows of buildings otherwise they would be wrongly classified due to spectral similarities. With the help of the “image object information” it was obvious how shadow image objects differ from others. Thereby, very low NDVI and brightness values were discovered. This information was used to build rules to assign affected image objects to the class “Gebäudeschatten”.

Afterwards, the image objects were analyzed with regard to the class “settlement”. The remaining unclassified image objects were classified with the help of the NDVI and the green band. The NDVI is a very powerful feature to distinguish between sealed and vegetated area. The applied low NDVI value classified the “sealed area” very well. However the NDVI lead to several wrongly classified image objects. Based on a visual impression the green band was used to reclassify them. A problem occurred with the thematic layer “wetland”. Segments situated at the border of the “wetland” image objects were wrongly classified as “settlement”, because the “wetland” layer did not fit perfectly to the data. Segments that are actually “wetland” were left unclassified. Thus, these segments were assigned to the class “settlement” because of their spectral similarities. Therefore, the neighborhood relationship of these segments of the classes “settlement” and “wetland” was used to reclassify them as “wetland”.
The remaining unclassified image objects were analyzed according to their membership to the class “forest land”. The NDVI was used to assign the image objects to the class “forest land”. This working step led to the fact that the entire vegetated area was classified as “forest land”. Lower green band values represented “forest land” very well, therefore it was used to reclassify wrongly classified “forest land” segments into unclassified. These errors occurred because of spectral similarities between the classes “forest land” and “grassland”.
The same NDVI value as before was used to classify the remaining image objects into the class “grassland”. A visual interpretation of the data showed that the red band was useful to reclassify wrongly assigned segments.
The remaining unclassified image objects that had an NDVI lower than 0.2 were assigned to the class “settlement”, the green band was used to assign unclassified image objects to the class “grassland”. The remaining unclassified image objects appeared in the classes “sealed” area” and “grassland”. The neighborhood relationship information of the classified image objects was used to classify those image objects that were still unclassified.

The following Figure 31 illustrates the process tree of the first image. The process tree contains all rules that were applied for the classification of the first image.

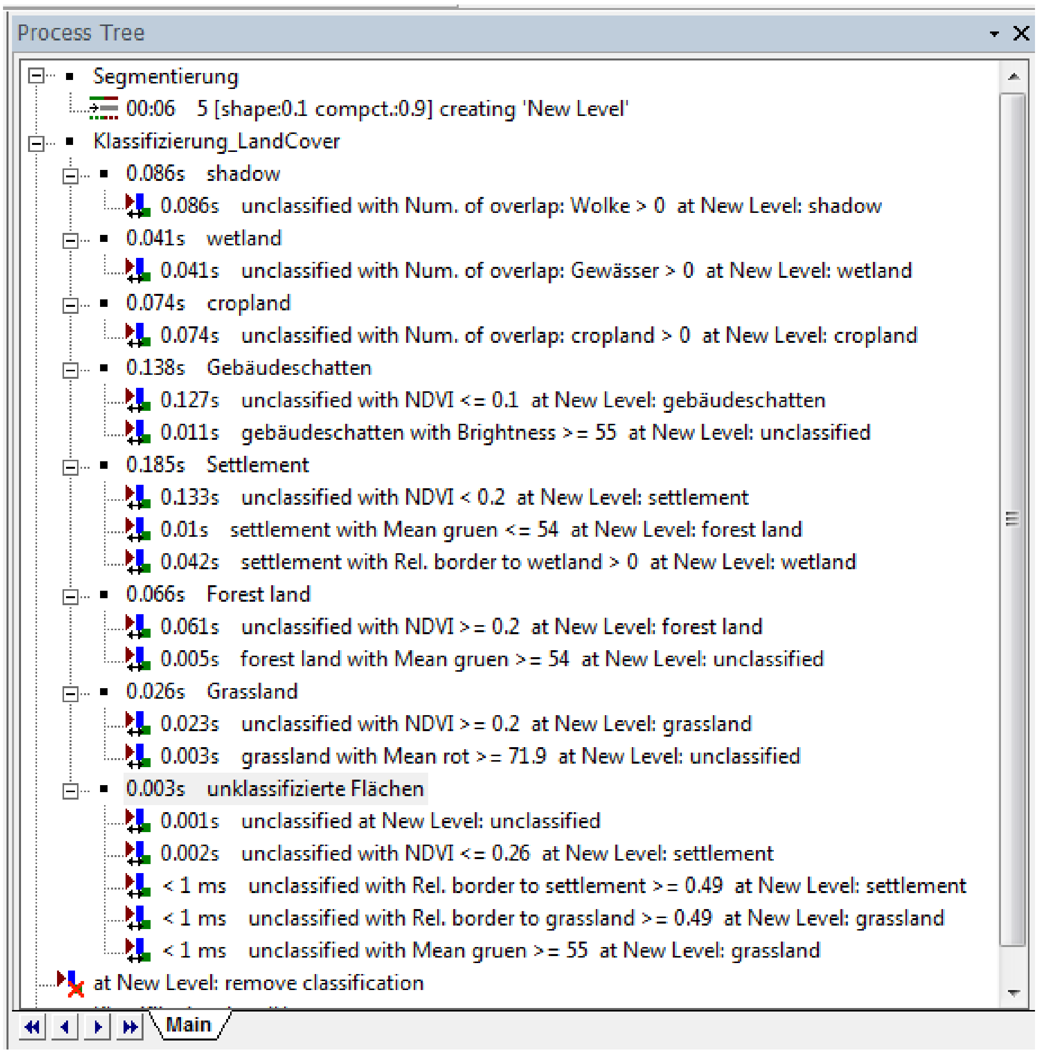


Figure 31: Process tree image 1. Source: own research in "Definiens Developer".

- Image 2

The first step was again the assignment of the unclassified image objects with the help of the thematic layers. Then, the unclassified image objects were classified with regard to the class "settlement". The red and green band and the NDVI were used to assign unclassified image objects to the class "settlement". A low NDVI value was applied to detect the sealed areas of image. But there were still unclassified image objects of the class "sealed area". Then the bands of the image were considered. It was obvious that the red band was suitable for the classification of "sealed area image objects". This working step led to fact that vegetated area was classified as "sealed area". A further consideration of the bands of the satellite image showed, that the green band was helpful to distinguish between sealed and vegetated area. Again the problem at the border of the wetland arose. To alleviate this problem, rules for the neighborhood relationship were applied. "Settlement" image objects with a border to those of the class "wetland" were reclassified as "wetland".

The NDVI was applied to classify the vegetated image objects. But due to the fact that a determination between "forest land" and "grassland" image objects is necessary, further rules had to be applied. After the consideration of the layer, the MIR band and the brightness information were used to distinguish between these two classes. Segments with a high MIR and brightness value were reclassified.

Next, the NDVI with the same value as before was used to classify unclassified image objects as "grassland".

The remaining unclassified image objects were assigned to the classes "settlement" and "grassland" with the help of the NDVI.

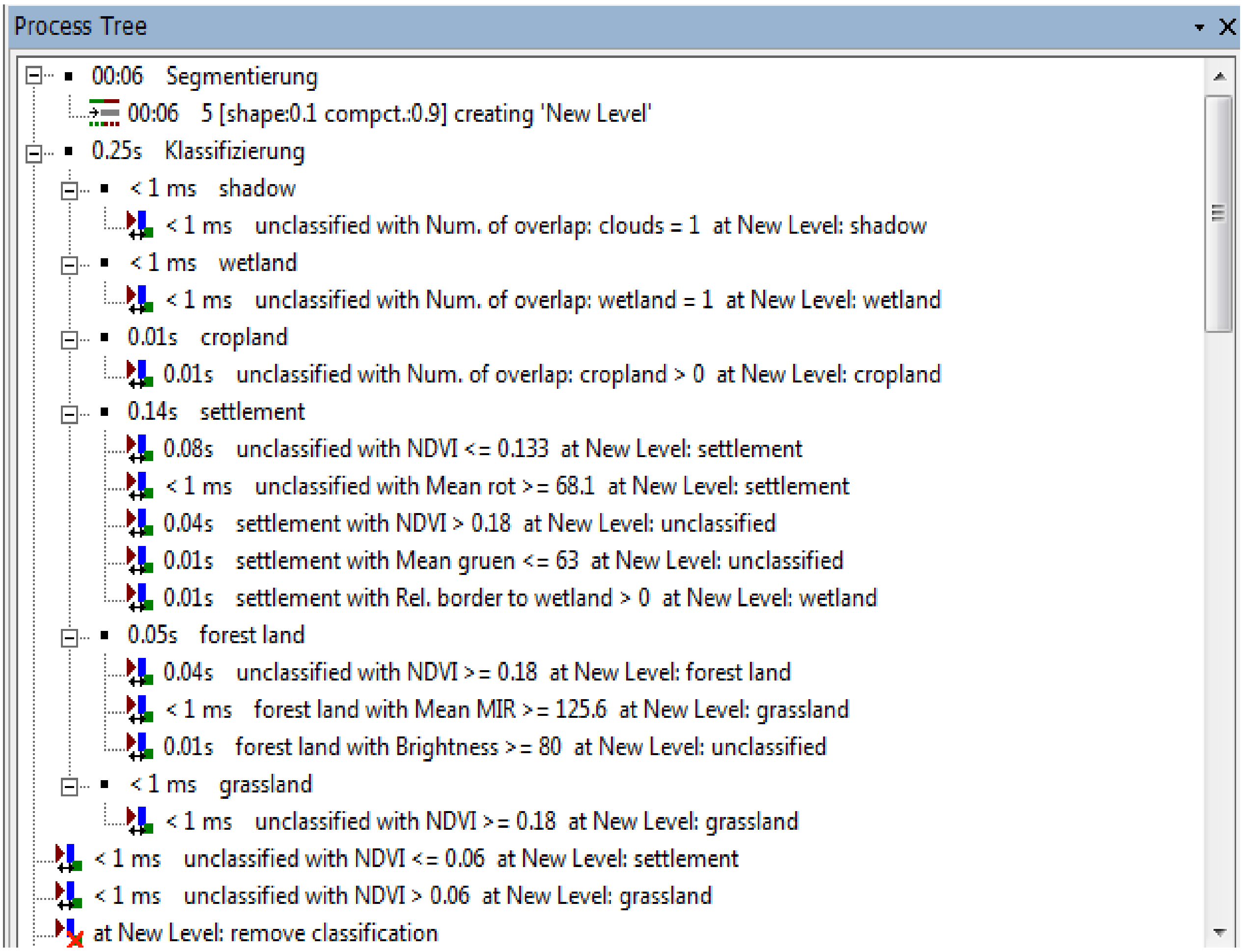


Figure 32: Process tree image 2. Source: own research in "Definiens Developer".

- Image 3

Primarily the unclassified image objects were assigned to a class with the help of the given thematic layers. The classification started with the class “settlement”. The defined rules were applied to the unclassified image objects and those of the class “cropland”, because there are buildings and other sealed areas within the cropland, until now they were all classified as cropland. However, there is the subclass “infrastructure within cropland” and therefore the affected image objects need to be classified as “settlement” in the land cover classification. In a first working step the layer values of the segments were considered. It turned out that the near infrared (NIR) and the red band are suitable for the classification of sealed area. A problem with the classification was that some “settlement” image objects were wrongly as “wetland”. Therefore, rules that concern the neighborhood relationships were applied. Those wrongly classified image objects of the class “settlement” that have a certain relative border to wetland were reclassified as “wetland”.

The remaining image objects were then classified with regard to the class “forest land”. Therefore rules were defined that used the NDVI and the red layer. The NDVI was able to distinguish between “forest land” and “grassland”. But there were still unclassified image objects that had to be classified as “forest land”. Based on a visual interpretation of the bands of the satellite image the red band was used for a further classification of “forest land” image objects. The visual interpretation of the bands showed that the green and the MIR band were suitable to eliminate image object of the class “forest land”. The affected image objects were reclassified as unclassified.

Still unclassified image objects were analyzed according to their membership to the class “grassland”. According to the visual interpretation of the bands of the satellite image the green band and the NDVI were used to assign unclassified image objects. The panchromatic layer was used to reclassify image objects that were wrongly classified as “grassland”.

The remaining unclassified segments were classified with the help of neighborhood relationships. The process tree of the third image is displayed in the following Figure 33.

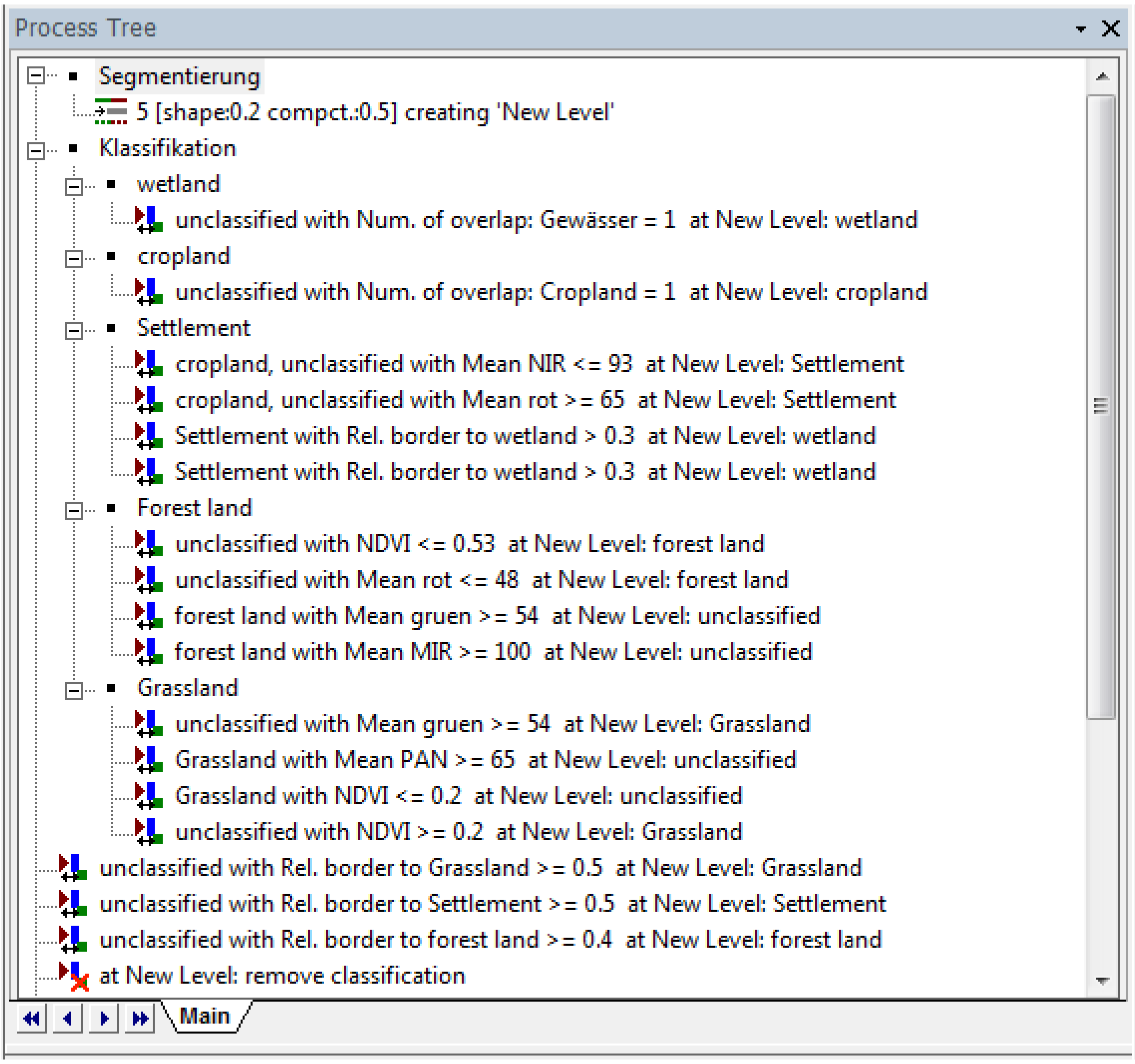


Figure 33: Process tree image 3. Source: own research in “Definiens Developer”.

- Image 4

After the application of the thematic layers, rules were defined to assign the image objects to the class “settlement”. As already explained the NDVI can distinguish very well between sealed and vegetated area. Unclassified image objects with a low NDVI were assigned to the class “settlement”. A visual interpretation of the bands of the satellite image showed, that the red band was helpful to reclassify wrongly assigned segments. Again the problem with the class “wetland” reappeared. Segments belonging to the class “wetland” were wrongly classified as “settlement” because of mistakes in the preparation of the thematic layer. Neighborhood relationships of the classes “settlement” and “wetland” were used to reclassify the affected image objects.

The NDVI was then applied to classify the segments that belong to the class "forest land". The visual interpretation of the layer values revealed that the green band and the brightness of the image objects can be used to reclassify those image objects wrongly classified as "forest land".

The NDVI was applied a third time to classify the vegetated but still unclassified image objects as "grassland". Due to spectral similarities, the asymmetry of the classified "grassland" image objects was used to reclassify them. Segments with a high asymmetry were assigned to the class "settlement". This feature is necessary to the classification process, because street segments are for example longer than other segments. The green band was also used to reclassify "grassland" image objects. The Figure 34 displays the process tree of the fourth image.

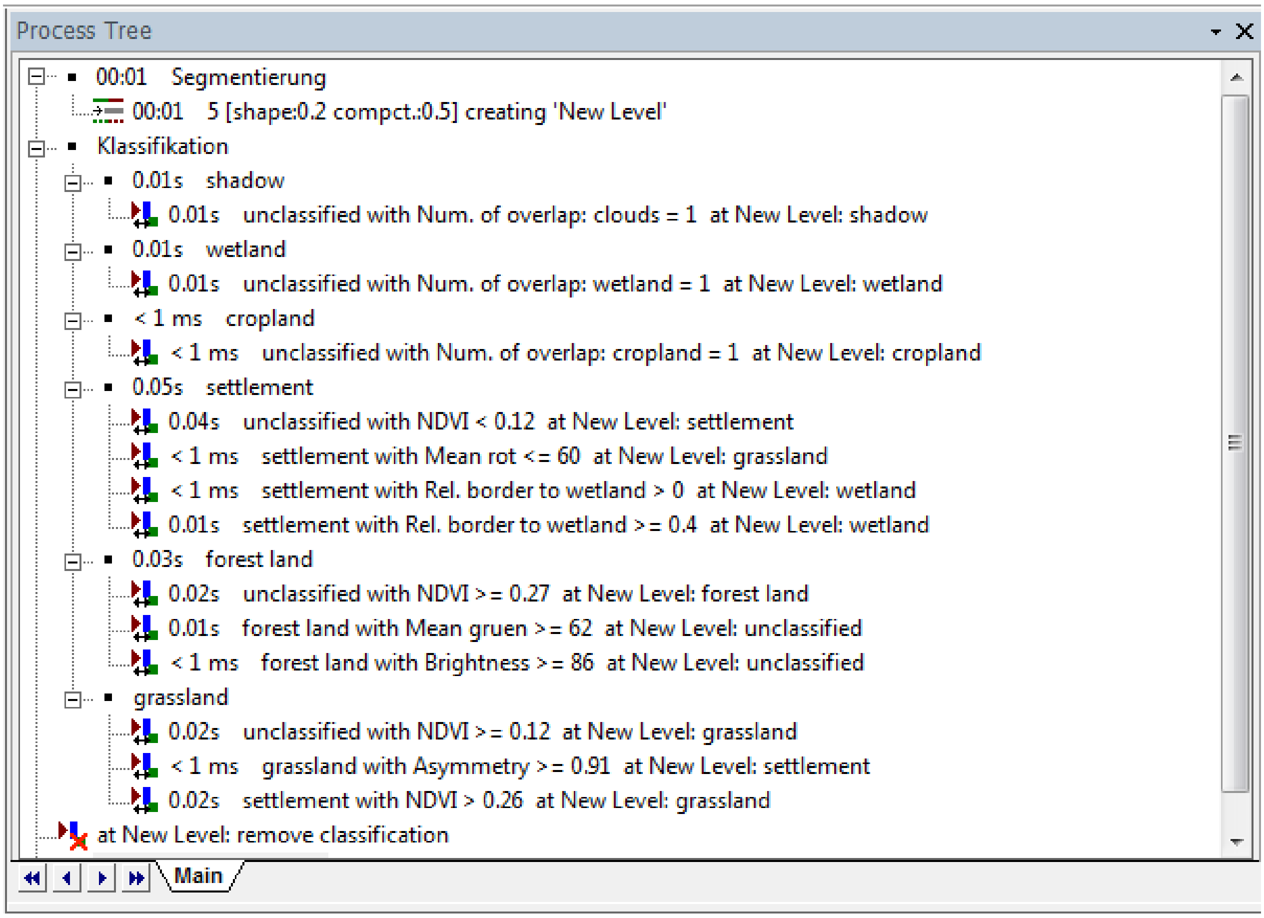


Figure 34: Process tree image 4. Source: own research in "Definiens Developer"

6.2.4.2. Classification of a combination of all four extracts

The aim was to combine the four sample images for a more effective classification result. A reoccurring problem emerged when the classifications of the single extracts did not fit for one another. Every extract required its own classification rules. The combination of the four images was therefore a compromise for the classification, because the single images differ with regard to atmospherical information. However, by combining them, a better resemblance of the whole investigation area was achieved. Due to the fact that the same rules were used for every image, the accuracy is limited and is not as reliable as the accuracy of the single extracts.

The software "ArcMap" was used to combine the four extracts into a new image. This step was done with the tool "Geo-referencing". The command "add control point" was used to merge all four extracts into one point. The coordinates of one corner point of an image were used to fix the corner points of the other three extracts to this point. Afterwards this new file was saved as a .tiff file. The geo-referencing step was also done for all three thematic layers. Figure 35 shows the result of the combination of the four images.

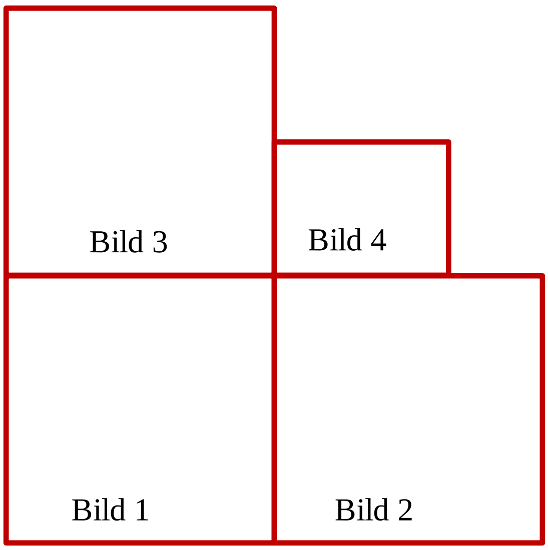


Figure 35: New image, combination of the four single extracts

This new data set was then loaded into the “Definiens Developer 7” software and a new project was created.

The combined extracts have an area with “no data” values, because the extracts do not have the same size. The concerned image objects have brightness values of 0. Therefore all segments that fulfil this condition were classified as “No Data”. Additionally, a merge region command was applied on these image objects, to create one large “No Data” polygon. Figure 36 shows the image objects, which are classified as no data and the result of the applied merge region function.

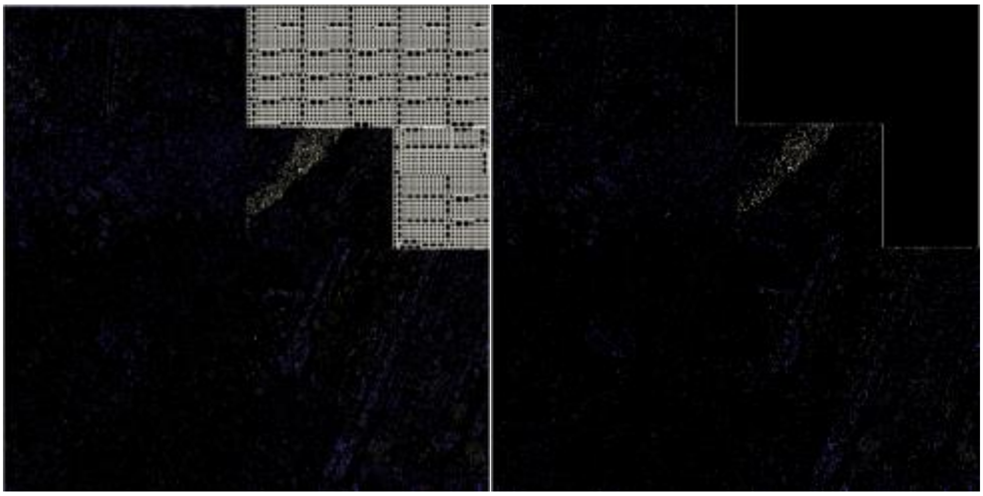


Figure 36: The left image shows the “no data” segments, the right result of the merge command. Source: own research in “Definiens Developer”.

Then, the image objects were primarily classified according to the thematic layers that are described in the chapter 6.2.4. Thus, all segments that were overlapped by clouds, wetland or cropland were assigned to the appropriate class.

The shadows of the buildings were classified in advance, otherwise they tend to be wrongly classified due to spectral similarities to the class “forest land”. All unclassified image objects with an “NDVI” value of 0.1 or lower were classified as “Gebäudeschatten”. However, wrongly classified segments occurred. Therefore another rule was defined. The information of the brightness criterion was used to reclassify the misclassified image objects as unclassified.

Then, the unclassified image objects from the class “cropland” that described a sealed area were assigned to the class “settlement”. Due to the fact that the class “cropland” can also include buildings and streets, these image objects need to be classified as “settlement” for a further processing. The NDVI was used to classify the urban areas of the image, but the applied rule led to wrongly classified image objects. Therefore, the green band was used to reclassify the false image objects as unclassified. Additionally, the “GLCM Homogeneity (all.dir)” was used to eliminate wrongly classified image objects. Similar to the single classification, a problem occurred because some of the “settlement” segments originally belonged to the class “wetland”. Due to the fact that the thematic layer “wetland” did not fit perfectly, the class “settlement” was misclassified. Therefore, the neighborhood relationships of the image objects of the classes “water” and “settlement” were used to reclassify the wrongly assigned image objects.

The remaining image objects with a higher “NDVI” value then the class “settlement” were assigned to the class “forest land”. However, this rule also classified image objects, which actually belong to the class “grassland”. Therefore, the red and the green image layer were used to reclassify wrongly assigned image objects.

The remaining unclassified image objects were classified as “grassland”. This step was executed without a rule, they were simply renamed. However, segments in the area of the cemetery were wrongly classified. Therefore, the panchromatic image layer was used to reclassify the image objects as “settlement”. Additionally, the “grassland” segments with a low “NDVI” value were reclassified as “settlement”.

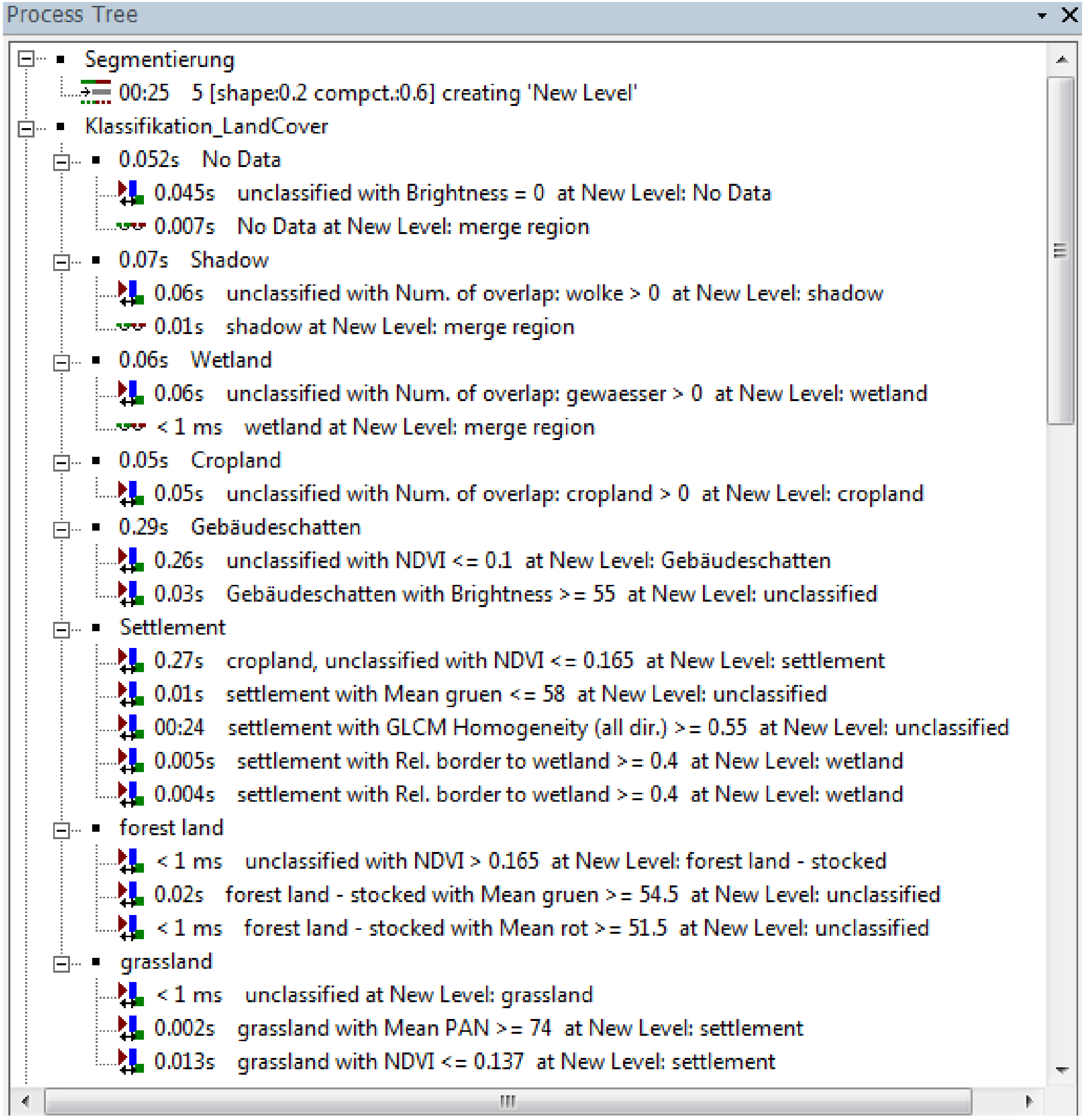


Figure 37: Process tree of the combined image. Source: own research in “Definiens Developer”.

6.2.5. Deriving land use information from the land cover classification

The Singapore project and therefore the work in the master’s thesis required the transformation of the land cover classification into a land use classification for the single image classification approach and the combined image approach. Therefore, the land cover classification rule sets of all projects were saved, because it was necessary to derive the land use from the land cover classification. For the land use classification, new projects the same adjustments as for the land cover classifications were established. The existing rule sets were loaded into the “process tree”, they were expanded with the rules for the land use.

Primarily, the class hierarchy was adapted to the land use classes. Five of the top level land use classes had several sub classes. The following Figure 38 shows the class hierarchy of the land use classification.

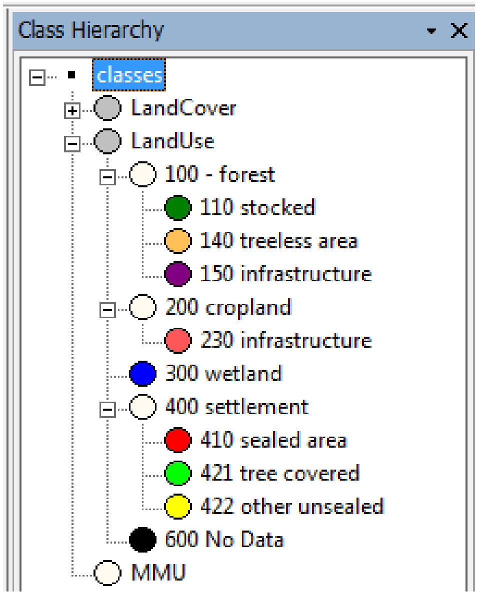


Figure 38: Class hierarchy – land use. Source: own research in "Definiens Developer".

The first step was to apply a merge region rule on all existing land cover classes because the area of the existing segments play a major rule with regard to the given minimum mapping unit (MMU). Sizes for some classes, for example "110 stocked" and "150 infrastructures within forest land" were given. The image objects belonging to the land cover class "forest land" and have an area of five hectares or larger were assigned to the class "110 stocked". Segments of the class "grassland" and "settlement" were analyzed according to their neighborhood relationship to the class "110 stocked". Rules were defined to assign image objects of these two classes, which were completely surrounded by segments of the class "110 stocked" to the appropriate sub classes. Image objects that were classified as "cropland" within the land cover classification were assigned to the class "200 cropland" without a rule. "Settlement" image objects within the cropland were assigned to the subclass "230 infrastructure". Image objects of the class "wetland" did not need rules for the transformation of land cover into land use. The segments were simply reclassified as "300 wetland". Image objects still classified as "forest land" and had an area smaller than five hectares were classified as "421 tree covered". Those segments that currently belong to the class "grassland" were simply assigned to the class "422 other unsealed area". Image objects still classified as “settlement” were reclassified as “410 sealed area”. Image objects that belonged to the classes “No Data” and “shadow” were assigned to the class “600 – no data”.

As previously mentioned, the existing image objects must exceed an area of 0.25 hectares. This size is defined as MMU and is true for the image objects of each class. The affected image objects were assigned to the class “MMU”. A merge region rule was applied on the “MMU” class, to merge nearby segments of this class. The neighborhood relationships of the “MMU” segments were concerned subsequently, and the segments of the class “MMU” were assigned to neighboring segments with a shared border ratio higher than 0.5 percent. A rule for every class was established to assign the “MMU” image objects to the proper class. In conclusion a merge region process was again applied on every class. Otherwise image objects within the classification that are smaller than the minimum mapping unit of 2500 square meters would still be present.

The resulting process tree was saved, because it served as a basis for the classification of the investigation area of Singapore. Then, it was applied to the tiles created within the following working step.

The Figure 39 shows the land use process tree of the combined image. However, the process trees of the single extracts were constructed in the same way.

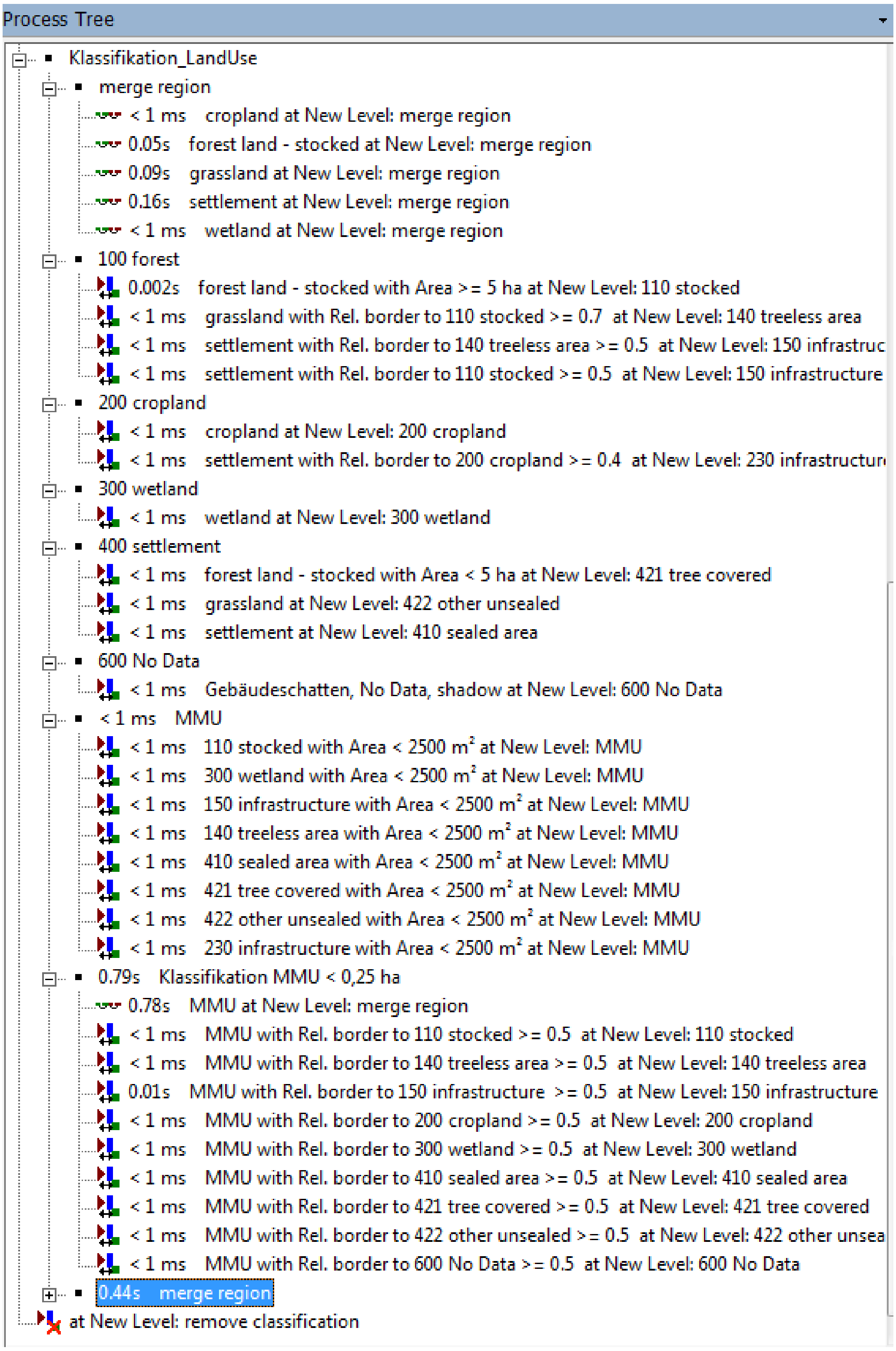


Figure 39: Process tree of the combined image classification. Source: own research in “Definiens Developer”.

6.2.6. Classification of the entire Spot 5 scene

6.2.6.1. Subdivision of the satellite image

The result of the classification of the combined image was the basis for the classification of the entire "Spot 5" satellite image. The combined image classification was chosen because of the better resemblance of the entire satellite image and to make the process more effective. The single image classification rule sets were not transferable to one another. The "Definiens Developer 7" was not able to edit the whole satellite image. Therefore it was necessary to part the whole scene into multiple parts within the "ArcMap" software.

The command "split raster" founded in "raster processing" in the "data management tool" was used to split up the whole satellite image. The input raster was the satellite image. It was then necessary to define the output folder and the output base name. The command "NUMBER_OF_TILES" was selected in the field split method. The user has the possibility to define the number of the tiles. Therefore, it is necessary to define X- and Y- coordinates. To receive 20 tiles, there are 5 tiles along the x-axis and 4 along the y-axis. This working step is also necessary for the panchromatic satellite image. Figure 40 shows the adjustments for the splitting of the remote sensing scene.

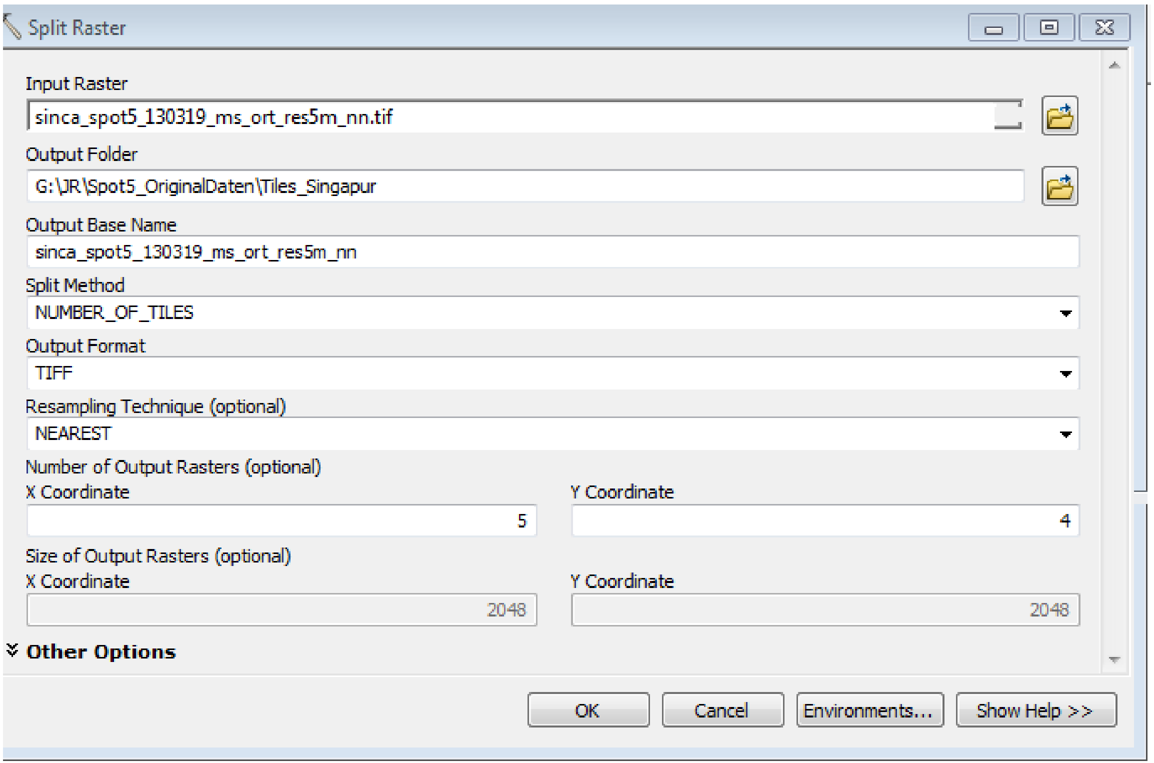


Figure 40: Splitting adjustments for the Spot 5 scene. Source: own research in "ArcMap".

Figure 41 shows the subdivision of the entire Singapore Spot 5 scene into 20 tiles.

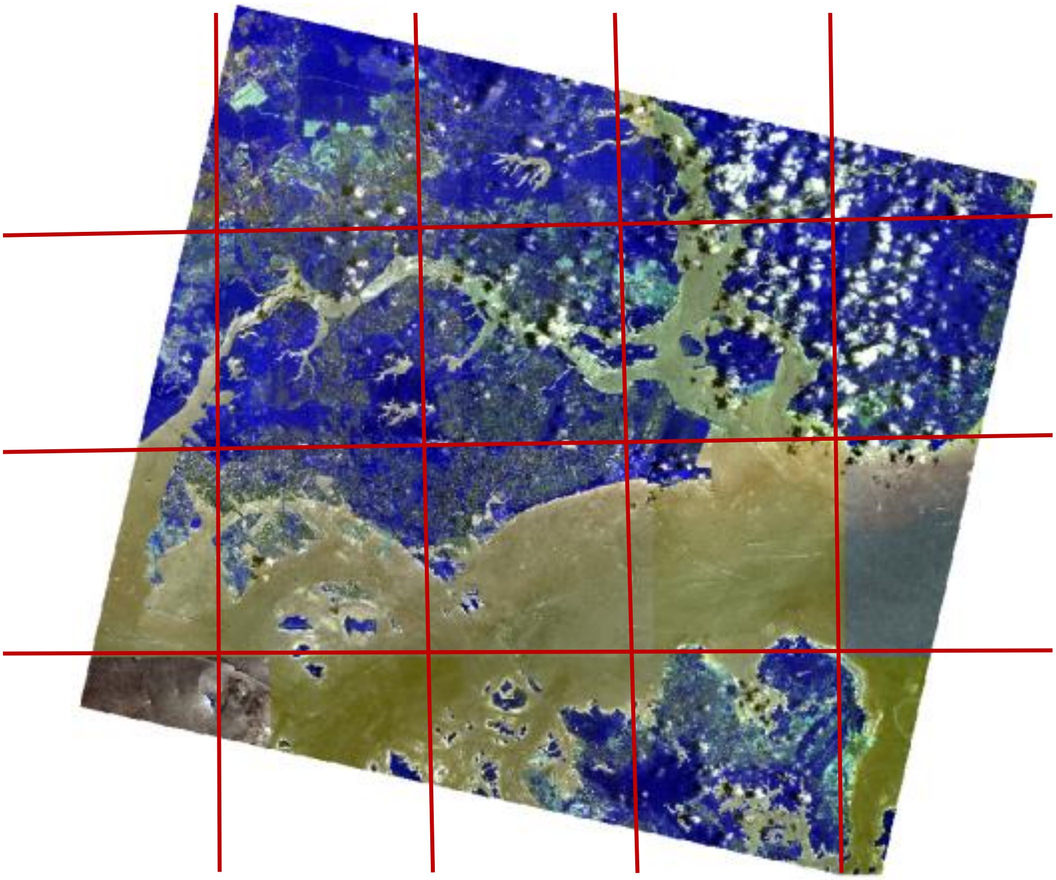


Figure 41: Subdivision of the Spot 5 scene. Source: own research in "ArcMap".

The "Erdas Imagine" software was used to combine the tiles of the multispectral and panchromatic tiles. The layer stack process was applied to the data. Within this process the four multispectral layers and the panchromatic layer were combined into a new image with five spectral layers. This working step was done for each of the tiles that represent Singapore.

6.2.6.2. Classification of the tiles

A new project was established within the "Definiens Developer" for each of these tiles. The applied segmentation was the same as for the segmentation of the combined image. The tiles were classified based on the process tree of the combined image. The results of the classification of the tiles were exported as shapefiles. This was necessary to further handle the data within "ArcMap" because the tiles were merged again to re-obtain an area containing all of Singapore.

6.2.7. Export of the results

The figure below shows an example of the adjustments to export a file in the “Definiens Developer” softwares. In the figure below it is obvious which class and feature information was saved within the shapefile. The output shapefile contained information on the class name of the class of the exported image objects and their size, length, and width.

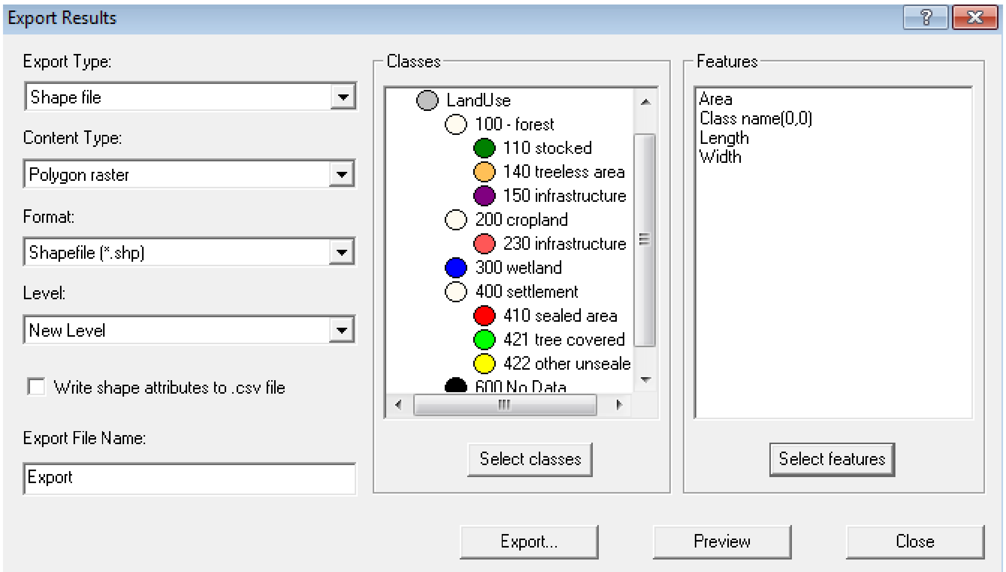


Figure 42: Export adjustments for the classification results within “Definiens Developer“. Source: own research in “Definiens Developer”.

The exported shapefiles of all tiles were loaded into the “ArcMap” software. The tool “merge” was used to combine the classification results of these tiles and to create a new shapefile.

6.2.8. Classification with the “Impact” software

6.2.8.1. Land cover classification

The land cover classification using the “Impact” software is a pixel based approach through which the spectral information of the pixels for is used for the classification. With the applied ISODATA method an unsupervised classification approach was used. 200 clusters were generated. A cluster number was assigned to each pixel. The pixels were then allocated to a label. The algorithm assigned labels to pixels and checked the most common code. Then the pixels were merged according to the MMU. Areas that did not achieve the defined MMU size of 2500 square meters, were merged with the best fitting neighbor according to spectra characteristics. The largest number of clusters belonged to the class sealed area, due to the high heterogeneity of the given remote sensing data. About 20 clusters belonged to the class wetland. It was not possible to apply a maximum likelihood classification approach on the data, because of the high heterogeneity.

6.2.8.2. Land use classification

The land use classification was derived from the land cover classification results. The neighborhood relationships played a major role. The four classes, high vegetation, low vegetation, sealed and wetland were defined. Several iterations were applied to the data. The easiest classification decisions were taken in advance. During the first cycle, forest land patches with a size of 5 hectares or larger were assigned to the class high vegetation. Water patches were always classified as wetland. The cropland was ignored, because a particular layer was prepared. Sealed area regions with a size of 0.5 hectares or larger were assigned to the class settlement. Elements with an irregular shape were separated into multiple autonomous parts. These parts were newly created, but maintained the same shape as before and were discrete elements.

The second cycle considers the neighborhood relationship of the elements, which were created during the first cycle. For example high vegetation elements were detected and the neighborhood elements were examined according to their probability of membership to the class high vegetation. Primarily, the probability of membership to the class needs to be for example 90% all elements that achieved this condition were reclassified. Elements that do not achieve the conditions remain as they are. During the next cycle, the probability was reduced. This classification principle was also true for the other classes, with the exception of the class “wetland”. Elements were never assigned to the class “wetland”.

7. Accuracy Assessment

7.1. Sample plot selection

The accuracy assessment was executed using the “ArcMap” software. The land use classification result was loaded into “ArcMap” and with the help of the “Feature Class” tool in the “Data Management” toolbox random points were created. The Figure 43 shows the “create random points” window. It was necessary to define the output file location and name. By using the “Constraining Extent” option, it was possible to load the basis for the calculation of the random points. The actual shapefile that included the land use classification. Then, random points were created according to the extent of the shapefile.

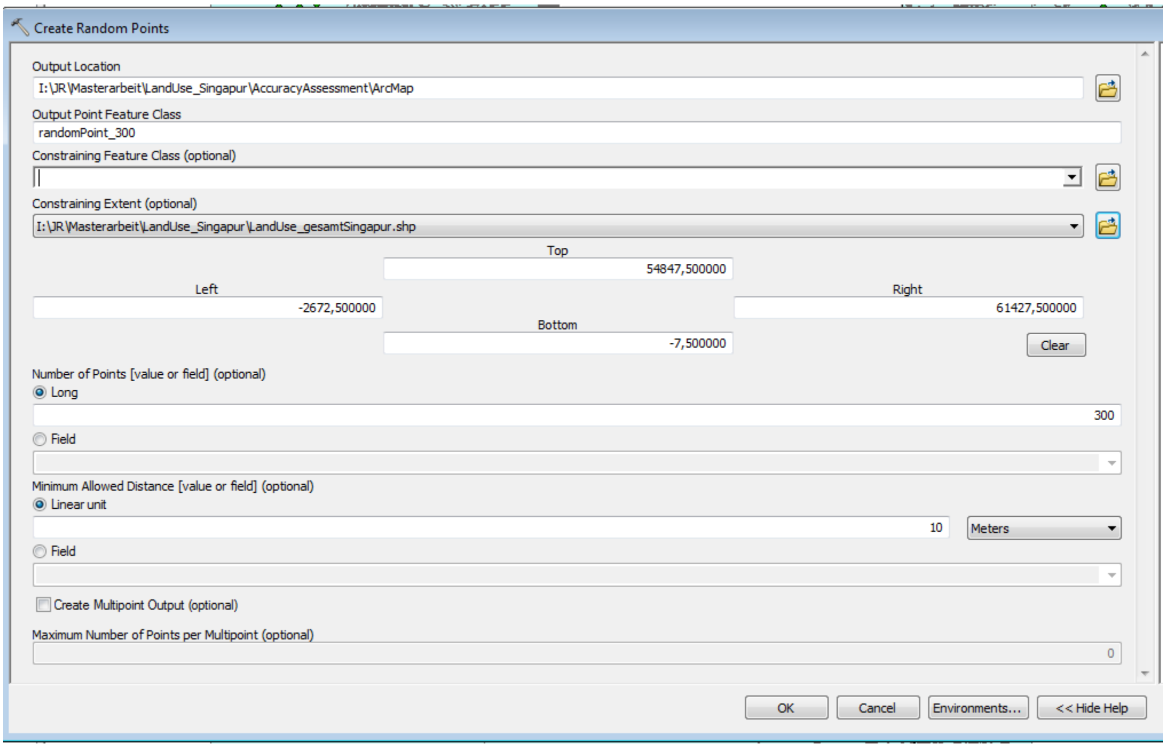
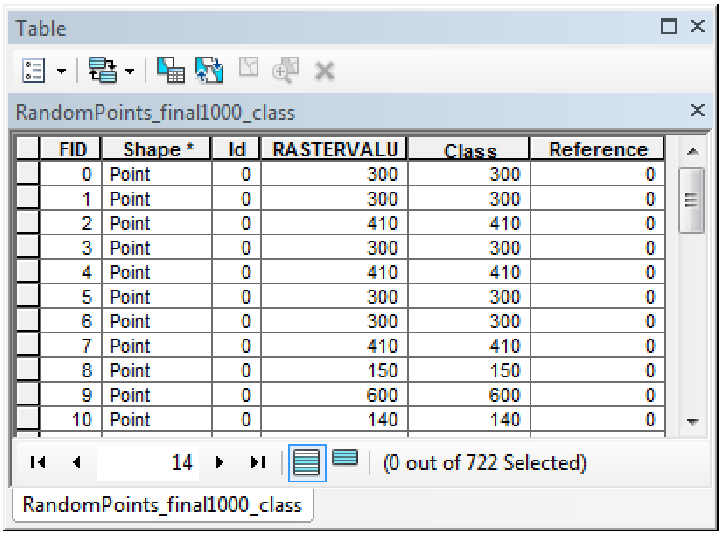


Figure 43: Create Random Points in “ArcMap”. Source: own research in “ArcMap”.

Then, the land use shapefile and the random points were loaded into “ArcMap”. The next step was to convert the shapefile, which contained the classification results, into a raster file. Due to the fact that each random point was situated on one image object, it was necessary to transfer the class information of the classification file on the random points. Therefore the command “extract values to points” within the “spatial analyst toolbox” was used. A new adjustment window opened where the random points and the classification file had to be selected. A new shapefile was generated, which contained the information of both files. Within the attribute table, each random point now clearly had the information of the classification result. A new column was added to the table to clearly define that the given “rastervalue” information was the actual class of the random point within the classification. The other added was necessary to compare the classification with the reference data. This column should contain the class of the random point from the reference data. The column “class” contained points that had the class number -9999, these random points were situated outside the classified area and were therefore deleted.



FID	Shape *	Id	RASTERVALU	Class	Reference
0	Point	0	300	300	0
1	Point	0	300	300	0
2	Point	0	410	410	0
3	Point	0	300	300	0
4	Point	0	410	410	0
5	Point	0	300	300	0
6	Point	0	300	300	0
7	Point	0	410	410	0
8	Point	0	150	150	0
9	Point	0	600	600	0
10	Point	0	140	140	0

Figure 44: Attribute table of the random points file. Source: own research in “ArcMap”.

The basemap provided by the “ArcMap” software was used as reference data for the accuracy assessment.

The world imagery map was updated in December 2014. For many parts of the world, the map offers a resolution of satellite or aerial imagery data of a resolution of one meter. For the representation of the world, 2.5 meter resolution Spot Imagery data is provided. Small scale or mid-scale areas are represented with 15 meter resolution TerraColor imagery data. (ARCGIS 2014)

The calculated random points and the “ArcMap” basemap were loaded into an “ArcMap” project. The points are automatically situated on the area of Singapore. A visual interpretation is applied. The user needs to zoom in to each point and compare the class of the classification of the random points to their position on the “ArcMap” basemap. The class information of the position of the random point will be registered in the reference column in the attribute table.

Figure 45: Random points in the basemap of "ArcMap". Source: own research in "ArcMap".

The classification result of the "Definiens Developer" and the result of the classification with the "Impact" software were compared to the reference data. Both comparisons used the same random points file. An error matrix was established for both classification approaches. These matrixes are displayed and interpreted in the chapters 7.2.1 and 7.2.2.

7.2.Results – Error Matrix

7.2.1. Error matrix of the “Definiens Developer” classification

Table 5: Error matrix of the “Definiens Developer” classification result

Reference Data													
Class		110	140	150	200	230	300	410	421	422	600	Total	user accuracy
Source data	110	39						2	17	11	8	77	50,65 %
	140	1	2						1	1	1	6	33,33 %
	150			1								1	100,00 %
	200	1			3							4	75,00 %
	230					0						0	0,00 %
	300	1					387	4		4	2	398	97,24 %
	410					1	1	121	7	8	3	141	85,82 %
	421							1	3	1		5	60,00 %
	422						1	8	8	35	1	53	66,04 %
	600	9					16	5	1	2	4	37	10,81 %
	Total	51	2	1	3	1	405	141	37	62	19	***722***	
	producer accuracy	76,47 %	100,00 %	100,00 %	100,00 %	0,00 %	95,56 %	85,82 %	8,11 %	56,45 %	21,05 %		**82,41 %**

In total 1000 random points were created with “ArcMap”, but only 722 of them were situated in the classified data. The largest number of random points concerning the source data represented the class “wetland” (300) with 398 points, followed by the class “sealed area” (410) with 141 points, 77 random points were situated on “forest land” (110) segments, 53 on “treeless area within sealed area”(140) and 37 random points represented the class “no data” (600). The classes with the lowest number of random points were “treeless area within forest land” (140) with 6 points, “tree stocked” within sealed area (421) with 5 points, “cropland” (200) segments with 4 points and “infrastructure within forest land” (150) with only one random point.

The low numbers of random points of some class’s resulted due to the fact that there were not many segments belonging to these classes. Additionally, the segments were relatively small, and therefore the random distribution of the points did not cover these segments. For example, for the case that the class 150 had to be smaller than 1 hectare and must be enclosed by the class “forest land” (110), the class “treeless area within forest land” (140) also had to be enclosed be the class “forest land”.

The results of the verification show that the classes “forest land” and “tree stocked area within sealed area” were represented as the same class. They differ from each other with regard to their size. In general these classes represent both forest lands. The same is true for the class “treeless area”. This class is a subclass of “sealed area” and “forest land”. The difference is that “treeless area within forest lands” needs to be completely enclosed by forest. It is difficult to distinguish between these classes although the “Definiens Developer” offers rules to apply neighborhood relationships. There are still wrongly classified image objects of these classes because of exceptions. It is difficult to make a statement as to whether the accuracy assessment had adequate results or not. This is due to the fact that the forest classes are incredibly similar to one another and 17 of the wrongly classified “forest land” pixels represent the class “421” in the base map. Using an applied visual correction some “forest land” segments larger than 5 hectares would be reclassified as “tree stocked within settlement” (421), because the forest segments are definitively no “forest land”. Within urban areas there are many allys, and these segments stick together. The applied “merge region” command often joins these segments into one big image object and together they built an image object larger than 5 hectares, which is therefore assigned to the class “forest land” although this is not true.

Another problem occurs with the class “infrastructure in cropland” (230). This class has the same spectral values as the classes “infrastructure within forest land” or “sealed area”. Without a visual correction it is not possible to distinguish between them. No random point was primarily classified as 230, after the comparison of the classification with the basemap, it turned out that one point of the class 410 belonged to the class “infrastructure within cropland”. Therefore, this class has a user and a producer accuracy of 0 %.

Only one of the random points was classified as 150, “infrastructure within forest land”. The user and the producer accuracy reached 100%, because the reference data and the classification are in accordance with one another.

The accuracy of the class 600 was in both cases significantly low, because the “Spot 5” data had included some clouds. Therefore, many areas of the image were classified as no data. The reference data however did not include clouds and the user accuracy was also low. Only four random points lied definitely on areas where clouds cover the surface of the earth. The producer accuracy was significantly low, because clouds also appeared within the basemap. However, these areas are different from the areas in the base map.

The overall accuracy of 82.41 % is an adequate result due to the fact that no visual correction was applied on the data. A classification based on a rule set does not suffice for an adequate determination between spectral similar classes. The rules that were defined to apply neighborhood relationships need to be better elaborated. Users with more knowledge about the software and its possibilities would achieve better results, because experience is an important factor for object based classification.

7.2.2. Accuracy assessment of the “Impact” classification

Table 6: Error matrix of the “Impact” classification result

	Reference Data												
Source Data	Class	110	140	150	200	230	300	410	421	422	600	Total	User accuracy
	110	75					5	3	8	10	15	116	64.66 %
	140		2	1				1	1	6	1	12	16.67 %
	150			1				1				2	50.00 %
	200				1							1	100.00 %
	230					1						1	100.00 %
	300	2					402	1	1	2	3	411	97.81 %
	410			1			3	119	6	4	3	136	87.50 %
	421							4	8	2	2	16	50.00 %
	422							6		11	3	20	55.00 %
	600	2						3		1	1	7	14.29 %
	Total	79	2	3	1	1	410	138	24	36	28	***722***	
	Producer accuracy	94.94 %	100.00 %	33.33 %	100.00 %	100.00 %	98.05 %	86.23 %	33.33 %	30.56 %	3.57 %		86.01 %

The generated random point file was also used for the verification of the classification with the “Impact” software of Joanneum Research.

The 722 random points were distributed in the following way: Concerning the source data, the largest number of random points represented the class “wetland” (300) with 411 points, followed by the class “sealed area” (410) with 136 points, and 116 random points were situated on “forest land” (110) segments. The class “treeless area within sealed area” (422) was represented with 20 random points, 16 random points were of the class “tree stocked” within sealed area (421) and 12 random points represented the class “treeless area within forest land” (140). The classes with the lowest number of random points were the class “no data” (600) with 7 points, the class “cropland” (200) represented by only one point as well as the class “infrastructure within cropland” with as well only one random point. Two random points represented the “infrastructure within forest land” (150).

Due to the fact that the same data and similar classification approaches were used, the same problems occurred. The classes “forest land” and “tree covered area within sealed area”, “infrastructure in forest land”, “infrastructure in cropland” and “sealed “area and “treeless area in forest land” and “treeless area in sealed area” are similar and therefore problems within the object based classification occurred. These classes can only be distinguished with the help of neighborhood relationships or visually. Additionally it is hard to differentiate automatically between “forest land” and “perennial crops”. Another problem were the defined MMU’s and the low number of generated random points for some classes and the size of the image objects of these classes. The smaller the segments the lower is the probability that a random point is situated on the image object.

The classes “treeless area within forest land” (140), “cropland” (200), “infrastructure within cropland” (230), wetland” (300) and “forest land” (110) achieved the highest producer’s accuracies. The classes “cropland” (200), “infrastructure within cropland” (230) and “wetland” (300) also show very good values in the user’s accuracy. Whereas the user’s accuracy of the class “treeless area within forest land” (140) is relatively low. The user accuracies of the classes “tree covered area within sealed area” (421) and “treeless area within sealed area” (422) are higher than the producer accuracies. An explanation for the lower producer accuracies can be that it is very difficult to classify these subclasses of the top level class settlement. The random point distribution did not cover many of these class segments, due to the fact that the size of these image objects was relatively small. Another problem is that the shadowed areas of buildings were wrongly classified as “tree covered areas within sealed area" (421) due to spectral similarities. The same is true for the class "treeless area within sealed area" (422).

7.2.3. Comparison of the error matrixes

The error matrix of the accuracy assessment of the "Impact" classification shows slightly different results than the accuracy assessment of the "Definiens Developer" classification. The classification result of the class "forest land" (110) is more accurate with the "Impact" software than with the "Definiens Developer". Whereas the class "treeless area within forest land" (140) has the same producer accuracies in both classification approaches. The classification of the class "infrastructure within forest land" with the "Impact" software is worse compared to the "Definiens Developer". The accuracy of the class "cropland" (200) is in both approaches the same for the user as well as for the producer accuracy. Contrary to the classification with the "Definiens Developer", the "Impact" software was able to classify image objects of the class "infrastructure within cropland" (230). The accuracy of this class amount to 100% and is again the same for the user as well as for the producer accuracy. The classification of the class "wetland" (300) had a higher accuracy with the "Impact" software with an amount of 98.05 %. The class "sealed area" (410) was only slightly better classified with the "Impact" software, the accuracy exhibited an accuracy of 86.23 %. The classification of the class "treeless area within sealed area" (421) was much better with the "Impact" software, than with the "Definiens Developer". However, the "Definiens Developer" software showed a better classification result for the class "treeless area within sealed area" (422) than the "Impact" software. The class "no data" (600) had better accuracy assessment values with the "Impact" software due to the fact that most of the clouded parts of the images were filled with "Landsata" data information previously.

The overall accuracy of the "Impact" software is with 86.01% better than the overall accuracy of the "Definiens Developer" classification result with 82.41%. A decisive reason therefore is amongst others that "Impact" software provided better classification results for the classes "cropland" (200) and "infrastructure within cropland" (230). Whereas the "Definiens Developer" was not able to classify the subclass of the top level class "cropland", the "Impact" software reached an accuracy of 100%. The rules concerning the neighborhood relationships applied within the "Impact" software are therefore better than within the "Definiens Developer".

7.3. Comparison of the classification results based on image examples

The results of the classification from “Defniens Developer” and “Impact”, the software of “Joanneum Research”, are compared in the following chapter based on image examples. Small extracts of all classification results were generated for a better comparison between the different approaches. Examples within urban areas, forest land, grassland, and cropland are shown. These extracts should give an impression where the object based classification approach produces good classification results and where problems occurred. The Figure 46 shows the occurring classes and their denotation.

110	Forest land –stocked
140	Treeless area within forest
150	Infrastructure within forest land
200	Cropland
210	Perennial Crops
220	Annual Crops
230	Infrastructure within cropland
300	Wetland
410	Sealed area
421	Tree covered area within sealed area
422	Treeless area within sealed area
600	No Data

Figure 46: Map legend of the following classification results

The different classification results are illustrated in a table. They are compared to the original satellite data and among themselves. Primarily, the satellite image extract is shown and then the results of the land use classification of the single extracts. The combined image and the extracts from the “Impact” software are faced. It is important to note, that none of these results were visually corrected. The applied land use classification results from the “Impact” software” is not the final data which was delivered to Singapore. The unedited “Impact” data was used for a better comparison, due to the fact that the “Definiens Developer” classification results were also not further visually edited. The finial data was additionally visually corrected and the image objects were edited because of the existing MMU of 2500 square meters.

- Urban area

+Table 7*:* Comparison of the classification of the urban area example

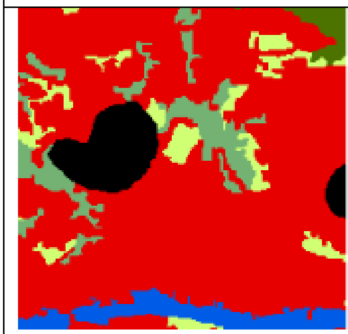
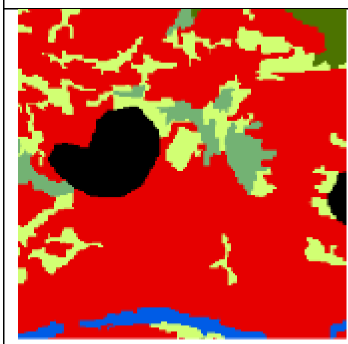
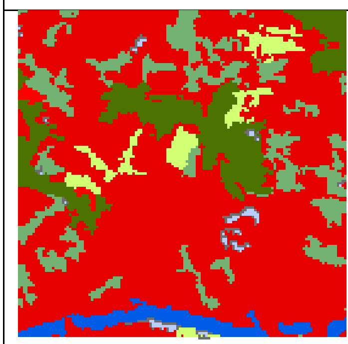
Original image	The orignal image gives the reader an impression of an urban area where shadows of buildings occur as well as tree covered areas and treeless areas. Additionally a part of a river is located in the image. The problem is the determination between the classes “forsest land” and “grassland”, it is obvious that these areas exhibit similar spectral information . The river was classified with the help of a thematic layer.
	
Classification single image	
	In comparison with the original image it is obvious that the class “sealed area” is too dominant within the classified image. The black image objects represent areas that are covered with clouds. Tthese were classified with a thematic layer. The river was also classified with the help of a thematic laye. Due to the applied region growing command, the borders are frayed. The “tree covered within sealed area” areas and the “treeless area within sealed area” are very well classified and distinguished.
Classification combined image	
	Within the combined image classification approach more “treeless area within sealed area” areas were classified than within the single image. Some “treeless area within sealed area” image objects are too large. Small tree allies were wrongly classified as “treeless area within sealed area”. The borders of the river are smoother due to the fact that no region growing command was used. In comparison with the single image, this classification is worse, because too many “tree covered within sealed area” image objects were classified as “treeless area within sealed area”. Again the class “sealed area” is too dominant.
Classification IMPACT 	Compared to the other classification results, it is obvious that many image objects that were above classified as “treeless area within sealed area” are here classified as “forest land”. This classes are better classified with the “IMPACT” software of Joanneum Research. The dark green elements represent the class “forest land”, compared to the original image it is obvious that these image objects are wrongly classified. These segments occur because the size of the image objects exeeds an area of 5 hectar. There are no black image objects because the clouded satellite areas were filled up with Landsat data. The river borders are frayed due to a region growing algorithm. The classification with “Impact” provides a better classification result than the “Definiens Developer”.

Table 8: Comparison of the classification of another urban area extract

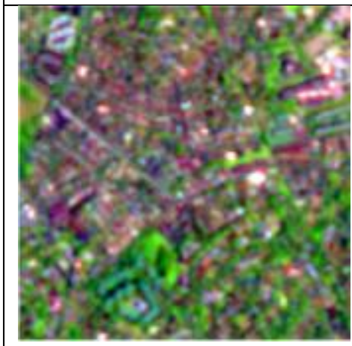
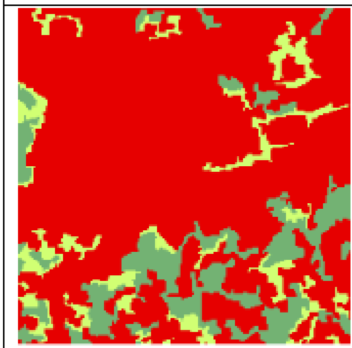
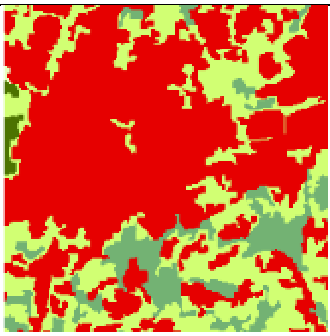
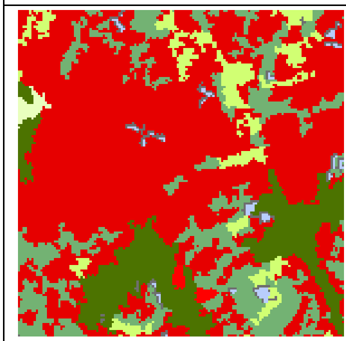
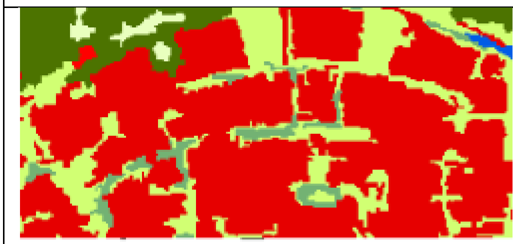
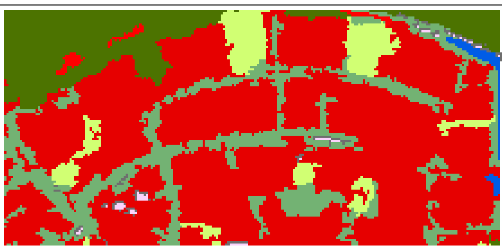
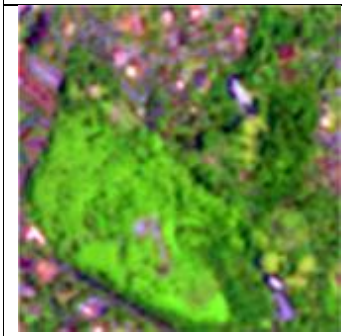
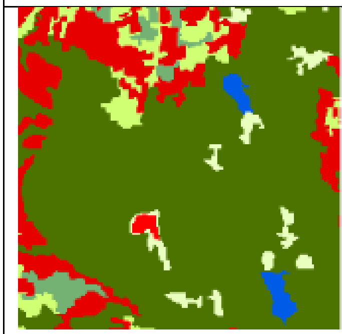
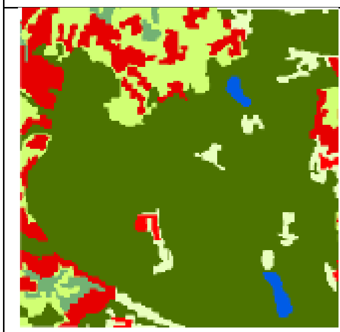
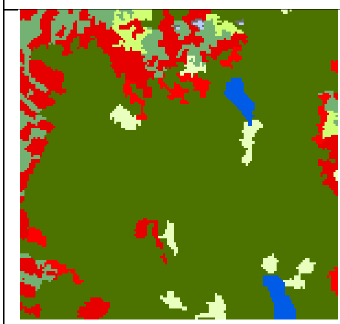
Original Image	
	This image shows “tree covered within sealed area” areas witin urban area. The problem is that these areas are mostly allies, which are small and thin. It is very difficult to detect them automatically, because the pixels are mixed. Another problem is the spectral similarity to the class “treeless area within sealed area”. In the lower right part of the image the problem occur, that the “tree coverered within sealed area” areas are dominant, but there are also “treeless area within sealed area” and “sealed area” regions that need to be classified.
Classification single image	
	The class “sealed area” is too dominant in the classification of the single image. Compared to the original image it is obvious that the “tree covered within sealed area” and the “treeless area wihin sealed area” regions are classified very well. The applied rules distinguish very good between these two classes despite spectral similarities. Only few tree covered areas are wrongly classified as treeless areas. In the lower right part of the image, the class “sealed area” is a little to dominant with regard to the original image. In the original image there are more tree covered areas than in the classification.
Classification combined image	
	Again the class “sealed area” is dominant within the classification, followed by the class “treeless area wihin sealed area”. But compared to the orignal image it is obvious that there are too much “treeless area wihin sealed area” image objects. The classification of the “sealed area” in the lower right part of the image is better than the single image classification, although there are too many image objects that are wrongly classified as “treeless area wihin sealed area”.
Classification IMPACT	
	The classification of the class “sealed area” is very good. It is obvious that there are two image objects that are classified as “forest land” due to the fact that the image objects are larger than 5 hectares. These image objects are wrongly classified, because the neighborhood is clearly dominated by “sealed area”. The large “forest land” segments resulted due to a merge region command. These wrongly classified “forest land” segments need to be visually corrected.

Table 9: Comparison of the classification of a third urban area extract

Original image	
	This extract is an example for “treeless area wihin sealed area” and “tree covered area wihin sealed area” within urban area. There are problems to detect the allies and to determine between the allies and the occurring green areas.
Classification single image	
	Compared to the original image it is obvious that too much of the area is classified as “sealed area”. The grassland regions in the original image were very well classified as “treeless area wihin sealed area”. A problem is the classification of the allies. The applied rules for the classifciation of the single image were not able to classify the allies.
Classification combined image	
	The applied rules for the classification of the combined image identified more vegetation. The rules detected the allies, but classified them as “treeless area wihin sealed area” and not as “tree covered wihin sealed area”. Grassland areas were again very well classified as “treeless areas wihin sealed area”. Regions in the upper left part of the image were wrongly classified as forest land. This error occured because of the size of the image objects that arose due to a merge region command. “Forest land” image objects within urban areas are usually “tree covered areas”. A visual correction is necessary to reclassify those image objects.
Classification IMPACT	
	Compared to the other classification results, the “IMPACT” software achieved the best result. The allies were very well detected as “tree covered wihin sealed area” areas and the grassland regions were also very well classified as “treeless area wihin sealed area”. As well as the classification result of the combined image, the “forest land” regions are wrongly classified. These regions are actually “tree covered” areas.

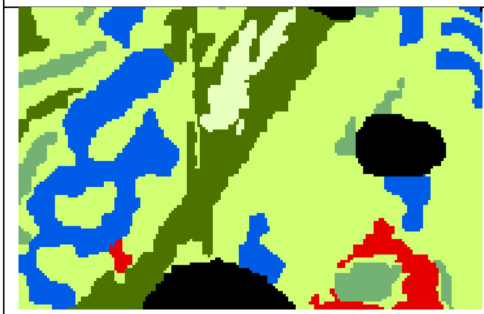
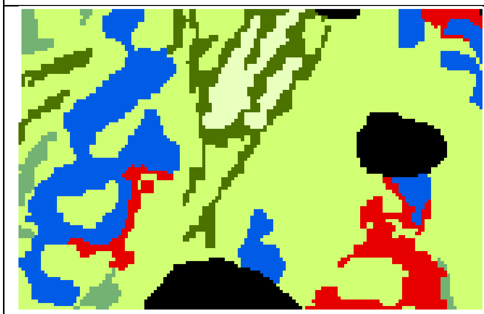
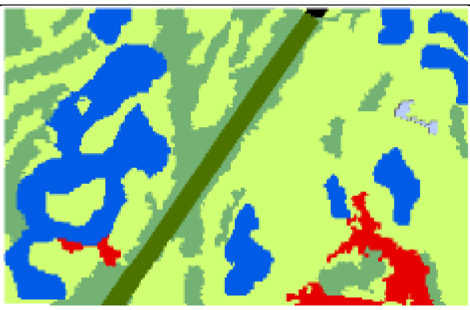
- Forest land

Table 10: Comparison of the classification of a forsest land extract in urban area

Original image	
	This extract shows an example for regions with different green values within an image. The dark green and the light green areas resemble forest land, but parts of the light green area also represent treeless area. This matter of fact is a challenge for an automated classification approach.
Classification single image	
	The classification of the single image detected the “forest land” regions and the “treeless areas within forest land” very well. Despite the different green values that represent “forest land” within the original image the applied rules classified the areas very accurately. The “sealed area” regions were also very well classified. Compared to the original image the class “treeless area within sealed area” is too domiant in the upper part of the image.
Classification combined image	
	The classification of the class “forest land” is very similar to the one of the single image. The classification of the “treeless area within forest land” image objects within the combined image is slightly different than the single image classification. Again the class “treeless area within sealed area” is too dominant in the upper part of the image. The classification of the “sealed area” image objects is adequate.
Classification IMPACT	
	Compared to the other classification results, the class “forest land” caputres more area of the image and is therefore slightly too dominant. The “treeless area within forest land” areas are again very similar to the other classification results and the original image. The classification with “IMPACT” exhibits not so many “treeless area within sealed area” regions, but therfore more “tree covered within sealed area” regions. Compared to the original image, too much of the area is classified as “tree covered within sealed area”. The classification of the class “sealed area” could be better.

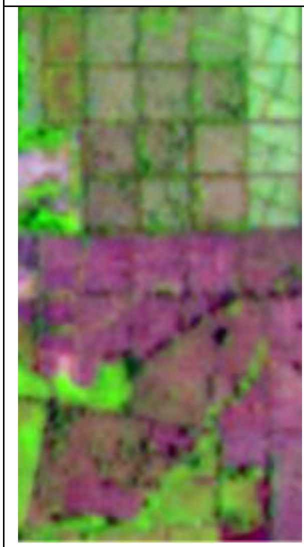
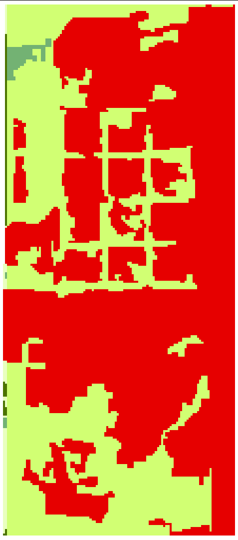
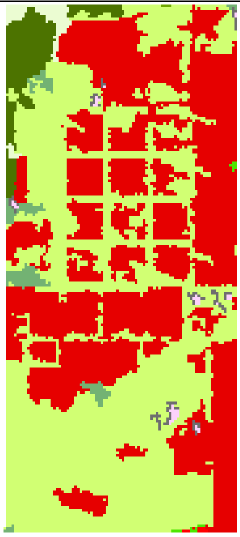
- Golf course

Table 11: Comparison of the classification of a golf course

Original image	
	This image represents a part of a golf course. The green area within the image should represent “treeless area within sealed area” and the trees should be classified as “tree covered area within sealed area”. The classification of the tree covered areas in the right part of the image is very difficult or even impossible, because the regions are very thin and therfore many mixed pixels occur. These areas are very similar to the class “treeless area”. The class wetland was again classified with the help of a thematic layer. Parts of the extract are slightly covered with clouds. A thematic layer was used to classify these areas.
Classification single image	
	Within the classification of the single image, the tree covered areas were wrongly classified as “forest land”. This error occurred due to a merge region command. Therefore the image objects reached a size of 5 hectares or larger and hence they were assigned to the class “forest land”. The grassland was very well classified as “treeless area within sealed area”. An error occurred because of the class “forest land”. In the upper part of the image it is obvious that an image object within the large “forest land” segment was wrongly classified as “treeless area within forest land”, due to neighborhood relationship classification rules.
Classification combined image	
	The tree covered areas within the golf course are again wrongly classified as “forest land”, due to their size. And again the image objcet within the “forest land” iamge object was classified as “treeless area within forest land”, because of the applied neighborhood rules. The grassland of the golf course was very well classified as “treeless area within sealed aera”.
Classification IMPACT	
	The clasification with the “IMPACT” software is better than the other classification results, altought there is one large and longish “forest land” image object. Compared to the original image the classes “tree covered area within sealed area” and “treeless area within sealed area” were very well classified. There are no clouds because, the clouded areas were cut out and filled up with Landsat data within preliminary work.

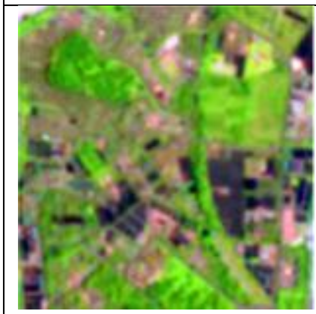
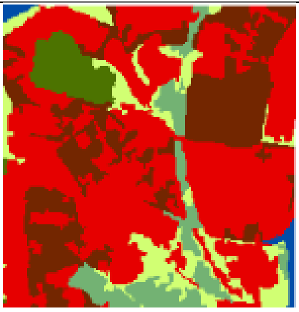
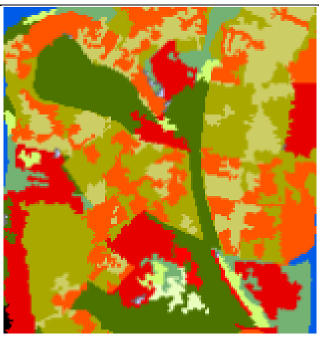
- Cemetary

Table 12: Comparison of the classification of an extract of a cemetary

Original image	Classification single image	Classification combined image	Classification IMPACT
			
The extract above shows a cemetery, but the spectral information within the image is different. In the upper part of the picture the cemetery is dominated by the color green but below it is purple. The problem is the classification as seald area despite the different spectral values.	The classification of the single image achieved a very good result.on this single image. The class “treeless area within sealed area” is too dominant in the upper left and the lower left part of the image.	Compared to the original image the class “treeless area within sealed area” is too dominant within the combined image classification. Another problem within the classification is the “forest land” image object in the upper left part of the classification. Compared to the orignal image it is obvious that there is definitively no “forest land” area within the image.	The classification with the “IMPACT” software performed also very well. Although the class “treeless area within sealed area” is too dominant in the lower part of the image. The vegetated areas within the class “sealed area” were very well classified. Again the area in the upper left part of the image was wrongly classified as “forest land”.

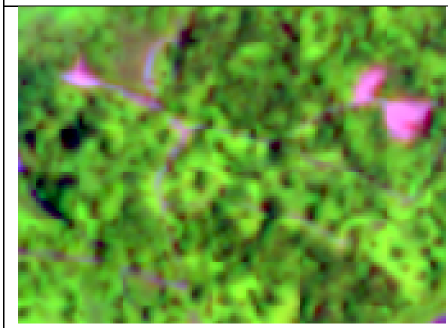
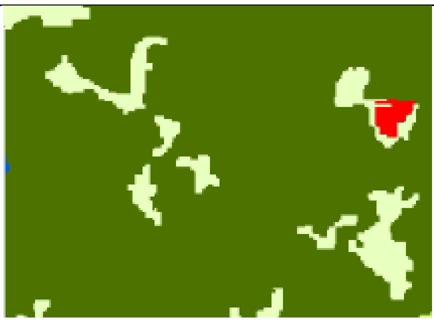
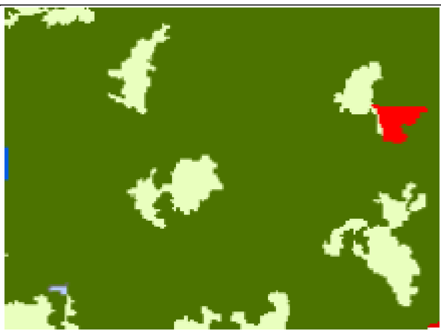
- Cropland

Table 13: Comparison of the classification of a cropland extract

Original image	
	This extract is an example for cropland. There occur problems in the classification, because it is not possible to determine perennial crops and tree covered areas automatically. Therfore a visual editing is necessary. Furthermore annual crops are protected with nets and therefore this areas are very dark and have spectral resamblance to fish ponds and also seald areas. Additionally it is not possible to determine between “sealed area” and “infrastructure within cropland” in the automatic classification.
Classification single image	
	The forest land region in the upper left part of the image was very well classified as “forest land”. The other tree covered areas within the image were correctly assigned to the class “tree covered area within sealed area”. Within the automated single image classification it was not possible to distinguish between the perennial and annual crops, therefore these regions were only classified as “cropland”. Another problem were the nets that protect the cropland, these areas were classified as “sealed area” as well as some fish ponds. These errors occurred due to spectral similarities.
Classification combined image	
	The forest land region in the upper left part was again very well classified as “forest land”. Compared to the single image classification the areas in the lower part of the image were wrongly classified as “forest land”. The other tree covered area was again correctly assigned to the class “tree covered area within forest land”. Compared to the single image classification more areas were classified as cropland. But the problems are the same as in the classification of the single image.
Classification IMPACT	
	The classification result of the “IMPACT” software differs from the other ones. It is obvious that there is a determination within the cropland. “Impact” was able to distinguish between “perennial crops” and “annual crops”. Additionally it was possible to assign the sealed area regions within the cropland to the class “infrastructure within cropland”. Compared to the other classification results it is obvious that the class “forest land” is too dominant. Only the forest region in the upper left part of the image is correctly classified.

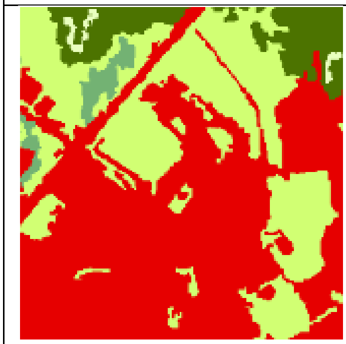
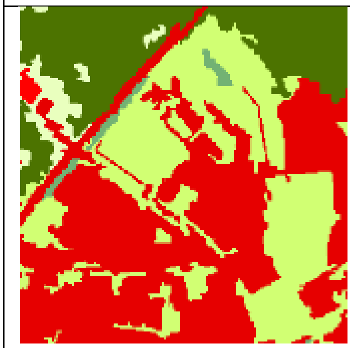
- Treeless area within forest

Table 14: Comparison of the classification of treeless areas within forest land

Original image	
	This extract is an example for “treeless areas” and “infrastructure within forest land”. The problem is the small size of some of these areas. Another problem are again the spectral similarities between the “forest land” and “grassland”.
Classification single image	
	The classification of the single image detected too much “treeless area within forest land” regions. Compared to the original imge, some of the detected “treeless area witin forest land” image object are wrongly classified. Actually some of them would belong to the class “infrastructure within forest land”. The same problem results in the upper right part of the image, a large infrastructure region was wrongly assigned to the class “treeless area within forest land”.
Classification combined image	
	The classification result of the combined image shows that the infrastructrue region in the upper right part of the original image was very well classified as “infrastructure within forest land”. But there occurred a problem within the upper left part of the image. A treeless area reagion was wrongly classified as “treeless area within sealed area”. This error occurred because of the neighborhood relationship rules. This error leads to another error, because image objects within this wrongly classified image object were also wrongly classified because of their neighborhood.
Classification IMPACT	
	Compared to the original image the result of the “IMPACT” software is very well. Altough there is again the problem of the determination of the classes “treeless area within forest land” and “infrastructure within forest land”. The classified “treeless areas within forest land” differ from the other classification results with regard to their shape. But the treeless areas of the original images are very well described.

- Forestland, grassland and sealed area

Table 15: Classification problems due to similar spectral circumstances

<table>
<tr><td>Original image</td><td></td></tr>
<tr><td></td><td>This image extract contains tree covered, grassland and sealed area regions. It is an example where the automated classification worked very well. In this example the spectral characteristics of the vegetated areas were different. The grassland areas are clearly obvious in the original image.</td></tr>
<tr><td>Classification single image</td><td></td></tr>
<tr><td></td><td>The “sealed area” regions were very well classified within the single image classification. Even a narrow path emerged in the classification. The class “treeless area within sealed area” was classified very well. Only in the upper left part of the image too much area was classified as “treeless area within sealed area”. The area in the upper left part of the original image is dominated by forest land. This result pictures the original image very well.</td></tr>
<tr><td>Classification combined image</td><td></td></tr>
<tr><td></td><td>The classification of the “forest land” in the combined image is better than the one of the single image. Altough there is slightly too much forest in the upper left part of the image. Combined to the original image the “treeless area within sealed area” image object should occupy more area. The class “treeless area within sealed area” is also very well classified. A classification error occurred within the “treeless area within sealed area”. It is obvious that there is one wrongly classified “tree covered” image object in the treeless area. And compared to the original image there is no “tree covered area within sealed area” in this area.</td></tr>
<tr><td>Classification IMPACT</td><td></td></tr>
<tr><td></td><td>The “forest land” area within the “IMPACT” classification result is again too dominant. Compared to the original image there is too less “treeless area” in the upper left part of the image. The “sealed area” classifications represent the situation within the original image very well. The same is true for the class “treeless area within sealed area”. Too many “tree covered” image objects were detected within the “sealed area” compared to the original image.</td></tr>
</table>

8. Reflection

This master's thesis aims to apply an object based classification approach based on a "Spot 5" satellite image for the stat of Singapore. The "Spot 5" image has a resolution of 2.5 meters in the panchromatic mode and 10 meters in the multispectral mode. The data was preprocessed within "ArcMap". The "Definiens Developer" software was employed for the classification of the data. The ultimate goal was to find out if the object oriented approach provides adequate classification results. Additionally it was of interest to compare the results of the "Definiens Developer" software with the "Impact" software from Joanneum Research. "Impact" uses the ISODATA method which is a pixel based classification approach for the land cover classification and an object based classification approach for the land use classification.

Two classification approaches based on "Definiens Developer" were applied in the master's thesis. Therefore the satellite image was split up in several smaller images. Four smaller images were selected for the further processing. Then, these four images were classified separately. As a result of atmospheric differences, four relatively different rule sets had to be applied. Therefore, it was not possible to transfer a general classification to the other images. In the second approach a combination of the four images was generated. Now the new image contains the atmospheric information and other characteristics of the four different and over the entire Spot 5 scene distributed images. The classification rule set of the combined image was used for the classification of the other generated tiles. After the classification of the single tiles, they were combined again with the help of the "ArcMap" software.

The object based classification is based on the segmentation of an image. During this process, the first uncertainties arise. The user must adjust the scale parameter and the homogeneity criterion. These two parameters can be defined arbitrary, because there is no ideal solution. Several combination methods must be explored to find the perfect adjustments for given data. This leads to the conclusion that a perfect judgment of the classification accuracy is not entirely possible. Different users would adjust the parameters in another way causing each result to be different. The user's experience plays a major role during the process of object based classification. Studies have shown that the parameters are similar in a majority of cases. The shape criterions exhibit a value between 0.2 and 0.4 and the smoothness and the compactness are both often valued at 0.5. The scale parameter depends on the given data and the goal of the classification. A more detailed classification requires a smaller scale parameter.

The segmentation process is followed by a rule based classification. The spectral, shape, and texture characteristics of the image objects as well as the neighborhood relationships were used to classify the images according to their land cover and land use. Image objects overlapped by wetland, cropland and clouds were classified with the help of thematic layers. These layers were generated with the “ArcMap” software in advance. It would not have been possible to classify the land use of the cropland, wetland, and clouds by using rules because of spectral similarities to the other classes.

Spectral similarities are another limiting factor that occurs within the rule based classification. Often distinguishing between “forest land” and “grassland” image objects is incredibly difficult. Image objects of the class “treeless area” that are dried out, exhibit spectral similarities to the class sealed area. Therefore, other features like the shape, texture and neighborhood relationships need to be considered. The problem is that no ideal rule set can be applied on every remote sensing image with the same resolution etc... Even in the different extracts of the same satellite image, it is not possible to assign the same rule set on each extract. This is a result of spectral values of an image differing due to atmospheric influences, different forest or grassland types etc…

To achieve better results a visual correction of the classification result is necessary. The problem with the “Definiens Developer” is that after a visual correction it is impossible to modify the rule set, because visual adjustments are lost when the classification is reloaded. This means that the visual adjustment must be the last step of the classification process.

It could be shown that the classification results are highly acceptable, although there is no guarantee that the parameters are adjusted adequately. The achieved accuracy assessment results are excellent, the overall accuracy is over 82 %. The producer accuracies are much better than the user accuracies. The remote sensing data contains areas covered by clouds, but the reference data has no clouds at the same position and vice versa. More experience with object based classification would have led to better results. The visual comparisons of the original Spot 5 data and the classification results show, that the classification was successful.

The comparison of the classification results of the “Definiens Developer” and the “Impact” software showed that “Impact” provided better results. “Impact” achieved an overall accuracy of 86%, which is excellent value. This states that the combination of a pixel based and object based approach within “Impact” leads to a better result than the pure object based method of the “Definiens Developer”. Another advantage of “Impact” is that the entire satellite image could be processed.

Nonetheless the object based classification method is an acceptable approach for the classification of remote sensing data. The option to apply spectral, shape, texture and context information as well as the neighborhood relationships gives the user many possibilities for the classification of images. Multiple attempts are necessary to find the best segmentation according to the given problem and data to be classified. Each data requires another access. The assumption that nearby pixels can be grouped together appears true, because they normally belong to the same class and can be merged. The shape characteristics offer many possibilities with regard to size and form. Street segments can be classified with the help of the length, or with asymmetry characteristics. Another major advantage of the object based classification is the neighborhood relationship of the image objects. Additionally, the sub-classes can be classified based on their neighborhood relationships to their associated main classes.

Although “Impact” provided better classification results, the object based method is an acceptable classification approach. Much research remains, especially regarding the segmentation of the remote sensing data. The better the remote sensing data, the better the object based classification results will be. The object based classification method suited very well for the creation of a land use map with Spot 5 data.

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